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Article

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The Impact of Big Data on SME Performance: A Systematic Review

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Abstract: Big Data (BD) has emerged as a pivotal tool for small and medium-sized enterprises (SMEs), offering substantial benefits in enhancing business performance and growth. This review investigates the impact of BD on SMEs, specifically focusing on business improvement, economic performance, and revenue growth. The objective of this systematic review is to evaluate the drivers and barriers of BD adoption in SMEs and assess its overall impact on operational efficiency and business outcomes. A comprehensive systematic review of 93 research papers published between 2014 and 2024 was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The methodology included detailed analysis of research approaches, addressing biases and gaps in the literature. BD adoption in SMEs led to significant improvements in operational efficiency, revenue generation, and competitiveness. However, the studies reveal persistent challenges, such as limited financial resources and technical expertise. The review identified a reporting bias, with 47% of studies using quantitative methods, 28% employing case studies, and mixed-method and qualitative studies underrepresented (22% and 17%, respectively). This imbalance highlights a potential overreliance on quantitative approaches, which may limit the depth of insights gained. While BD offers considerable potential for driving innovation and enhancing competitiveness in SMEs, addressing the current methodological biases and resource-related barriers is crucial to fully harness its benefits. Future research should focus on diverse approaches to provide a holistic understanding of BD's impact on SMEs.



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Keywords: Big Data; small and medium-sized enterprises (SMEs); business performance; economic growth; data-driven innovation; systematic review

1. Introduction

Data have become a fundamental asset, shaping how businesses operate and strategize globally. The rise of digital technologies has triggered an immense surge in the amount of data generated across different platforms, such as social media, online shopping, and various digital tools. This phenomenon, known as Big Data, offers businesses extraordinary opportunities to gain insights into their internal processes, customer behaviors, and the broader market landscape [1]. For small and medium-sized enterprises (SMEs), which are crucial for economic development and innovation, the ability to harness Big Data is especially important. By adopting Big Data, SMEs can convert large datasets into practical intelligence, enabling them to refine business strategies, improve marketing effectiveness, boost competitiveness, and enhance overall performance. However, effectively utilizing Big Data is not without challenges, particularly for smaller companies that may lack resources and expertise [2–4].

Despite the clear advantages of data analytics, its adoption among SMEs remains lower than expected, especially when compared to larger organizations that are more actively embracing Big Data for decision-making and performance optimization. Several

factors contribute to this slow adoption [5–7]. Financial limitations pose a major hurdle, as the costs associated with implementing and maintaining sophisticated data analytics systems can be prohibitive for smaller firms. Additionally, many SMEs lack the technical knowledge required to fully utilize Big Data. The complexity of Big Data tools, combined with the shortage of skilled professionals, further aggravates the challenges SMEs face. Organizational culture also plays a significant role in the adoption of new technologies. In many SMEs, traditional attitudes can create resistance to change, making it difficult to integrate data-driven approaches into existing business models [8–10].

A key challenge for SMEs is their lower level of technological maturity. Unlike larger companies, which often have well-established IT infrastructures and dedicated teams for managing data initiatives, SMEs may still rely on outdated systems with limited technological capabilities [11]. This lack of advanced technology not only hinders their ability to collect and analyze data effectively but also impedes overall digital transformation. Larger enterprises, by contrast, benefit from economies of scale, enabling them to invest in cutting-edge technologies and attract skilled professionals, creating a stark difference in Big Data adoption between SMEs and their larger counterparts. To better understand the differences in Big Data adoption between SMEs and larger organizations, established theoretical models such as diffusion of innovation (DOI) and the technology–organization–environment (TOE) framework provide valuable insights. The DOI theory suggests that SMEs may be slower in adopting Big Data due to their limited resources and higher sensitivity to external pressures, such as market demand or financial risks [12]. The TOE framework further helps explain how Big Data adoption is shaped by three key factors: the technological, organizational, and environmental contexts in which a firm operates. SMEs face significant technological and organizational barriers compared to larger enterprises, which may contribute to their slower adoption of Big Data solutions [13–16].

Given the significant role of SMEs in the global economy, addressing these challenges is essential. SMEs make up most businesses around the world and are key drivers of employment, innovation, and economic growth. As the digital economy grows, the ability of SMEs to remain competitive will increasingly rely on their capacity to utilize data-driven insights [17–19]. However, existing research on Big Data adoption in SMEs is limited, with most studies focusing on larger enterprises. This gap is concerning, especially as SMEs need to adapt quickly to the demands of the digital era. Without a clear understanding of the specific factors influencing data analytics adoption in SMEs, they risk being left behind in an increasingly competitive market [13,14]. This systematic literature review aims to fill this gap by analyzing the impact of Big Data on SME performance. Through a review of existing research, the study seeks to identify the key drivers and barriers that affect data analytics adoption in SMEs. The review will focus on challenges such as financial constraints, lack of technical expertise, organizational culture, and technological maturity, exploring how these factors shape SMEs' ability to leverage Big Data [14,15]. Additionally, the review will assess the broader impact of Big Data adoption on SME performance, highlighting potential benefits in terms of innovation, competitiveness, and responsiveness to market changes. This analysis will provide valuable insights for academic researchers and SME managers alike, offering practical recommendations to overcome barriers and improve SME performance through Big Data [15,16].

Ultimately, this research adds to the ongoing discussion on information systems and technological innovation by emphasizing the critical role of Big Data in the future success of SMEs. By focusing on the specific challenges and opportunities unique to SMEs, the review provides a fresh perspective on the factors influencing Big Data adoption in smaller businesses [17,18]. The findings will inform future research and policy aimed at supporting SMEs in their digital transformation. Additionally, these insights will be invaluable for SME managers as they navigate the complexities of Big Data, enabling them to build more data-driven organizations and remain competitive in the global market. As SMEs continue to face the pressures of digital transformation and increased competition, their ability to harness Big Data will be a key factor in determining their success moving forward [19,20]. Table 1

presents a comprehensive review of various studies focusing on the role of Big Data, analytics, and digital transformations in small and medium-sized enterprises (SMEs). It covers key aspects such as contributions to the field, theoretical frameworks, and identified research gaps. The table aims to highlight critical pros and cons of each study while identifying areas where further research or analysis is necessary. By examining comparative insights and gaps, this review contributes to understanding how Big Data adoption, analytics, and related technologies impact SMEs, particularly in operational, financial, and competitive performance. This structured analysis also incorporates different theoretical frameworks, such as the technology–organization–environment (TOE) model, to provide a multi-dimensional view of SME transformations. Each study is critically evaluated to determine its strengths, limitations, and how this review builds upon those findings to fill existing gaps, offering a more comprehensive perspective for future research.

Despite the substantial body of research on Big Data adoption, there remains a significant gap in integrating these studies into a cohesive theoretical framework, particularly one that accounts for the unique challenges faced by SMEs. While many studies explore the benefits and obstacles of Big Data, few systematically contextualize their findings using established technology adoption models, such as diffusion of innovation (DOI) or the technology–organization–environment (TOE) framework. These models are particularly relevant to understanding the barriers to Big Data adoption in SMEs, as they address key dimensions like organizational readiness, technological complexity, and external pressures factors especially pertinent in the resource-constrained environments typical of SMEs.

The TOE framework stands out as a powerful tool for understanding SME-specific challenges, as it highlights how organizational context, technological capabilities, and environmental factors collectively influence technology adoption. By more thoroughly engaging with this framework, future research could provide a clearer understanding of how SMEs navigate the complexities of adopting Big Data, especially in comparison to larger enterprises with greater resources and infrastructure. For instance, SMEs often face issues such as limited technical expertise, financial constraints, and a lack of organizational support—barriers well captured by the TOE framework. Integrating this model into the theoretical discussion offers a structured way to assess how SMEs can overcome these barriers and leverage Big Data to enhance their innovation capacity and competitiveness.

Additionally, there is a lack of empirical research exploring data-driven innovation and digital transformation in SMEs, particularly in developing countries. These regions often experience additional challenges, such as underdeveloped digital infrastructure and limited access to cutting-edge technologies, which can hinder the effective adoption of Big Data. Incorporating more recent research on digital transformation in these contexts would strengthen the theoretical foundation and provide actionable insights for SMEs in similar environments. By focusing on how these businesses can implement Big Data in ways that drive innovation and improve performance, research could offer practical solutions tailored to the distinct constraints and opportunities faced by SMEs in developing economies.

There is a pressing need to build a clear conceptual framework that directly links Big Data capabilities with performance outcomes in SMEs, emphasizing innovation, operational efficiency, and competitive advantage. Such a framework should address not only technological and organizational factors but also consider external market pressures and the broader competitive landscape. By developing this framework, future research can offer a more nuanced understanding of how SMEs can utilize Big Data to transform their business models, enhance decision-making processes, and ultimately gain a sustainable competitive edge. Integrating theoretical models like TOE, DOI, and the concept of data-driven innovation offers a comprehensive approach to understanding the full impact of Big Data on SMEs, creating a more robust and cohesive foundation for future studies.

Table 1. Comparative analysis of existing reviews and proposed systematic review.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[21]	1583	2016	Developed a Big Data Capabilities (BDC) model integrating management, technology, and talent dimensions, validated through Delphi studies and surveys.	Highlights the importance of aligning analytics capabilities with business strategy; provides a hierarchical model of BDC.	Lacks detailed empirical evidence on the direct impact of BDC on firm performance; potentially limited generalizability of findings.	Gap—BDC’s performance impact leaves questions about its true efficacy. Our review’s contribution—We build on this by providing more detailed performance metrics for SMEs, focusing on how different BDCs affect operational and financial performance.	Not specified
[22]	233	2017	Proposed a Big Data adoption model for Indian firms using PSV and TOE frameworks.	Insights into Big Data adoption in emerging economies; practical for managers.	Limited generalizability; small sample.	Gap—Study’s focus on Indian firms limits its applicability globally. Our review’s contribution—We extend the geographical scope, comparing Big Data adoption models in SMEs from diverse regions to provide more globally applicable insights.	TOE framework
[23]	54	2018	Review of Big Data as a source of competitive advantage.	Identifies key benefits and sources of competitive advantage from Big Data and practical implications for various industries.	Requires managerial awareness for effective implementation; focuses on conceptual benefits without in-depth empirical analysis.	Gap—Conceptual focus lacks real-world testing. Our review’s contribution: We add validation of how Big Data creates competitive advantages in various SME contexts through comparison with our findings.	Not specified
[24]	50	2019	Examined the early-stage adoption of Big Data in international marketing, especially in SMEs and developing countries.	Provides insights into the current state of Big Data adoption and highlights future research directions.	Limited research on Big Data adoption in international marketing, especially among SMEs in developing countries.	Gap—The lack of depth on specific SME challenges in international contexts. Our review’s contribution: We focus specifically on SME performance and Big Data in global supply chains, addressing gaps in international marketing contexts.	Not specified

Table 1. Cont.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[25]	3	2019	BI in decision support systems.	Enhances decision-making quality, supports strategic decisions, and improves efficiency.	Requires complex setup, can be costly, and data integration challenges.	Gap—Lacks detailed insights into cost-benefit analyses for SMEs. Our review's contribution—We incorporate cost-performance metrics in SMEs using innovative financial models, filling this gap.	Not specified
[26]	24	2020	Review of decision-making (DM) and knowledge management (KM) in small transport SMEs, proposing new assessment tool.	Highlights DM–KM benefits for SMEs, especially in transportation.	Limited empirical evidence on SMEs in transportation; research relies on literature.	Gap—Limited practical insights and empirical backing for the assessment tool. Our review's contribution—We propose new, empirically tested models, addressing gaps in DM–KM integration in SMEs beyond transportation.	Not specified
[27]	54	2021	Comprehensive identification of the impact of open innovation on company performance through a systematic literature review.	Provides a clear picture of the importance of organizational readiness for open innovation.	Focuses primarily on the management domain, potentially limiting applicability to other fields.	Gap—Open innovation's practical application in sectors beyond management is underexplored. Our review's contribution—We assess the intersection of Big Data and open innovation in SMEs, including practical examples across sectors.	Not specified
[28]	108	2021	Review and bibliometric analysis of Big Data adoption.	A broad analysis of Big Data across sectors; highlights research gaps and trends.	Limited to English-language studies; may miss relevant research due to keyword selection.	Gap—Limited to English-language studies, which may overlook non-Western perspectives. Our review's contribution—We integrate research from multilingual databases, offering a more comprehensive global perspective.	Not specified

Table 1. Cont.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[29]	159	2021	IoT and Big Data in supply chain decision-making: a review.	Promotes autonomous decision-making and distributed data processing.	Challenges in fully leveraging IoT-generated data for SCM decisions due to limited autonomy.	Gap—Lack of detailed case studies on IoT-Big Data integration. Our review's contribution—We include case studies of SMEs successfully adopting IoT-Big Data solutions for supply chains, providing actionable insights.	Not specified
[30]	15	2021	A systematic review of Big Data adoption challenges in Malaysian SMEs.	Highlights Lessig's four modalities' relevance and SMEs' challenges insights.	Limited to Malaysian SMEs; focus on literature review rather than empirical data.	Gap—The study's narrow focus on Malaysian SMEs restricts broader generalizability. Our review's contribution—We expand the scope to address adoption challenges across multiple countries, enhancing its global relevance.	TOE framework
[31]	25	2022	Analyzed the impact of inventory management on SMEs' operational performance using bibliometric and systematic review methods.	Revealed trends and gaps in inventory management research. Identified emerging themes and technologies.	Limited to articles only in English and from Scopus; some papers only addressed IM or OP separately.	Gap—Limited depth in combining IM and operational performance studies. Our review's contribution: We propose best practices that link directly to operational and financial performance in SMEs, adding depth.	Not specified
[32]	11	2022	Development of a Big Data adoption model in B2B, four-category classification, systematic literature review.	Comprehensive, structured approach; clarifies adoption motives; broad view identifies research gaps.	Lacks practical details, may miss contexts; too theoretical, lacks empirical validation.	Gap—Too abstract, lacking practical applications. Our review's contribution—We provide real-world applications of Big Data models in B2B SMEs.	TOE framework
[33]	246	2022	Overview of Big Data in intelligent manufacturing; proposes a decision-making framework.	Provides theoretical basis and practical insights; highlights real-time dynamic perception.	Limited to one year; may not cover emerging technologies beyond 2021.	This review's contribution is narrow in terms of timeframe and lacks depth on sustainability aspects. The proposed review bridges this gap by extending the analysis to long-term sustainable impacts on SMEs.	Decision-making framework

Table 1. Cont.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[34]	3	2023	Examined factors influencing the adoption of Big Data in SMEs, identifying 13 key factors.	Provides a thorough analysis with practical insights; enhances academic understanding; useful for SMEs.	Focuses mainly on SMEs and may overlook some emerging trends or factors.	While this study provides a focused analysis on SMEs, it lacks quantitative performance metrics. The proposed review contributes by introducing various frameworks to assess SME performance using Big Data.	TOE framework
[35]	19	2023	Analyzed COVID-19 impact on SMEs' supply chains.	Provides current insights.	Limited to a specific population.	The COVID-19 context limits generalizability. The proposed review broadens the scope beyond pandemic-related impacts to offer broader insights into Big Data and sustainability in various sectors.	Not specified
[36]	111	2023	Reviewed the use of data science in SMEs' digital marketing strategies. Identified seven state-of-the-art uses and proposed four future research directions.	Provides a comprehensive overview of current data science applications in SMEs; identifies gaps and future research areas.	Limited to existing literature; may not fully capture emerging trends in data science.	While this study focuses on digital marketing, the proposed review expands to multiple business functions within SMEs, such as operations and supply chain, to provide a holistic perspective.	Not specified
[37]	9	2023	A systematic review of Cloud ERP, linking enablers and barriers to innovation outcomes.	A thorough analysis of benefits and challenges; a useful framework; identifies future research areas.	Limited to literature up to February 2022; primarily based on Indian studies; lacks some empirical data.	The narrow focus on Cloud ERP and its regional limitations are addressed in the proposed review by encompassing a wider range of technological setups and geographical contexts for SMEs.	TOE framework
[38]	161	2023	Identified initial steps for MSMEs in digital transformation.	Empowers MSMEs, fosters innovation, and enhances reputation.	Requires cultural change and stakeholder management.	This study emphasizes cultural aspects of digital transformation, but lacks a deep dive into performance metrics. The proposed review fills this gap by providing detailed performance indicators and innovative models for evaluation.	Not specified

Table 1. Cont.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[39]	0	2024	Examines how Industry 4.0 skills impact sustainable manufacturing in SMEs, highlighting rational culture's moderating effect and stressing the need for these competencies to boost sustainability.	The study offers insight into how Industry 4.0 competencies can boost sustainable manufacturing for SMEs, identifies literature gaps, and underscores the moderating role of rational culture.	The study's focus on Malaysian SMEs may limit its broader applicability, and reliance on existing literature might overlook recent Industry 4.0 and sustainable manufacturing trends.	The proposed review expands the scope to cover broader contexts, including non-manufacturing SMEs, and introduces performance metrics to track the impact of Big Data in fostering sustainability.	Not specified
[40]	6	2024	Reviews the impact of inventory management practices on SMEs' operational performance through bibliometric and systematic analysis.	Highlights key inventory management strategies, identifies research gaps, and provides a roadmap for future studies.	Focuses broadly on inventory management without in-depth analysis of specific practices or technologies.	While the study provides valuable insights into inventory management, it lacks integration with other business processes. The proposed review addresses this by examining how Big Data applications can optimize various SME operations.	Not specified
[41]	2	2024	Examines cloud computing's role in the circular economy for SMEs using TOE and institutional isomorphism frameworks.	A comprehensive framework identifies research gaps and rigorous methodology.	Limited empirical data on cloud computing's impact, and complex framework.	This review is narrow in focus (cloud computing), whereas the proposed review integrates multiple technologies like Big Data, Cloud, and IoT to offer a more comprehensive view on SME transformation.	TOE framework
[42]	0	2024	Explores the negative implications of Industry 4.0 on sustainability and presents a framework for addressing these issues.	Highlights Industry 4.0's negative impacts like job losses, wage gaps, and environmental issues, and suggests ways to address them.	The emphasis on negative impacts may overshadow Industry 4.0's benefits and relies mainly on Indian literature with limited empirical data.	The proposed review takes a balanced approach, discussing both positive and negative implications of Industry 4.0 on SMEs, while offering innovative financial models to better assess outcomes.	Not specified

Table 1. Cont.

Ref.	Citations	Year	Contribution	Pros	Cons	Critical Gaps and Comparative Insights	Theoretical Framework
[43]	1	2024	Systematic review of integrating analytics in enterprise information systems (EISs).	A comprehensive review of global literature; highlights adoption challenges and strategic impacts; utilizes PRISMA 2020 and TOE framework.	May overlook non-English-language studies; Limited by selected databases and search terms.	The focus on EIS limits generalizability across all SME setups. The proposed review contributes by examining diverse Big Data applications across different SME sectors to provide a holistic understanding.	TOE framework
[44]	50	2024	Systematic review of business analytics for competitive advantage in emerging markets.	Comprehensive analysis of recent literature; identifies key impacts and challenges.	Excludes non-English-language and non-peer-reviewed sources; limited to recent publications.	This review focuses on business analytics in general, whereas the proposed review narrows in on specific Big Data applications in SMEs to provide more targeted, actionable insights.	Not specified

1.1. Research Questions

In this research, we investigate the influence of Big Data on the efficiency of small and medium-sized enterprises (SMEs). The study delves into how Big Data can improve SMEs' functioning, highlighting both the advantages and obstacles faced in its application. The following research questions aim to provide insights into these aspects to better understand the effective use of Big Data in SMEs' performance:

- How does Big Data capability impact SMEs' performance?
- What are the critical factors influencing the successful implementation of Big Data in SMEs?
- How can awareness and understanding of Big Data be leveraged to enhance productivity in SMEs?
- What are the challenges SMEs face in integrating Big Data into their existing systems and operations?
- How can SMEs effectively adapt their decision-making processes to harness the full potential of Big Data analytics?

1.2. Research Rationale

The rapid advancement of information and communication technologies has resulted in a significant increase in data generation, offering businesses opportunities to remain competitive. However, simply investing in Big Data (BD) tools is insufficient—companies need the capabilities to manage and effectively utilize these large data volumes. This challenge is particularly pronounced for small and medium-sized enterprises (SMEs), which play a vital role in global economies, but often lack the resources and expertise necessary to adopt Big Data technologies successfully.

While Big Data has the potential to enhance business innovation, competitiveness, and decision-making, SMEs face substantial obstacles, such as the absence of clear strategies, inadequate skills, and weak organizational cultures that hinder successful BD implementation.

To address these challenges, this systematic review adopts the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to comprehensively analyze existing research on Big Data's impact on SME performance. By synthesizing studies published between 2014 and 2024, the review aims to identify key drivers and barriers to BD adoption, explore gaps in the current research, and provide actionable insights for SME leaders and policymakers. This approach ensures a thorough evaluation of available evidence, helping to better understand how SMEs can leverage Big Data for operational efficiency, innovation, and competitiveness.

1.3. Research Objectives

The primary objective of this systematic literature review is to explore the influence of Big Data (BD) on the efficiency and performance of small and medium-sized enterprises (SMEs), with a focus on enhancing operational effectiveness, fostering innovation, and improving competitiveness. This review systematically examines the literature to identify key trends and assess critical factors driving or hindering BD adoption within SMEs. By employing a systematic review methodology, this study aims to provide a structured and comprehensive understanding of the most influential studies, key themes, and emerging trends in this area.

This review also investigates how an increased understanding and awareness of BD can boost SMEs' productivity and facilitate business expansion. By examining the impact of BD on decision-making processes, this study offers insights into the factors that enable or hinder the integration of BD within SMEs. These insights will serve as valuable recommendations for business leaders and policymakers, supporting the promotion of effective digital transformation strategies. The review's approach ensures a rigorous synthesis of available research, providing a clear path for future studies in the rapidly evolving fields of Big Data and digital transformation in SMEs.

1.4. Research Contribution

This study investigates the role of Big Data (BD) in enhancing the performance of small and medium-sized enterprises (SMEs), particularly in relation to BD capabilities and knowledge management (KM) practices. The research makes the following significant contributions.

- This research establishes BD adoption as a crucial enabler of innovation for SMEs operating in resource-constrained environments. In these contexts, BD adoption extends beyond operational efficiency, acting as a catalyst for innovation. By leveraging data-driven insights, SMEs can overcome limitations in financial, human, and technological resources. This study highlights how BD can be strategically utilized as an innovation resource, allowing SMEs to develop dynamic capabilities and foster continuous innovation despite their size and limitations.
- A key contribution of this study is the proposed conceptual frameworks for various industries that demonstrate how BD capabilities, alongside KM practices, positively influence SME performance. The framework underscores the importance of integrating technological infrastructure with managerial support to maximize the impact of BD adoption. Additionally, KM practices act as mediators, amplifying the effects of BD on innovation and competitiveness. This integration emphasizes the need for a techno-human collaboration that combines data-driven insights with KM systems to drive sustainable competitive advantage.
- This research introduces a taxonomy categorizing SMEs based on their level of BD adoption—low, medium, and high adopters. Low adopters rely on basic analytics for operational decisions, while medium adopters integrate BD with KM practices to gradually enhance performance. High adopters leverage BD for strategic innovation, transforming business models and enabling the development of new products or services. This taxonomy provides SMEs with a clear roadmap to assess their BD maturity level and offers practical implications for implementing advanced data-driven strategies.
- This study provides actionable insights for SME practitioners by demonstrating how BD can enhance both operational and long-term innovation performance. The findings serve as a practical guide for SME managers to strategically adopt BD, optimizing not only their efficiency but also fostering a culture of innovation that strengthens their market competitiveness. The study offers a structured approach for integrating BD with KM practices, enabling SMEs to unlock the full potential of data-driven decision-making.

1.5. Research Novelty

This research makes a novel contribution to the field by addressing a critical gap in the literature. While existing studies have explored the benefits of BD for large enterprises, there has been limited examination of its adoption and impact in SMEs. This systematic review comprehensively evaluates the influence of BD on SME performance, focusing on the key factors that either facilitate or hinder its adoption.

The study identifies underexplored areas, such as the financial constraints, lack of technical expertise, organizational culture, and technological readiness that impede SMEs' ability to harness BD. By addressing these specific challenges, the research provides targeted insights and practical recommendations that are directly applicable to the SME context. This contribution helps SMEs better integrate BD technologies, improving their operational performance and enhancing their ability to compete in the data-driven business landscape.

2. Materials and Methods

This section outlines the steps for carrying out a review of how Big Data influence the effectiveness of small and medium-sized enterprises (SMEs). The review examines studies from the past decade, particularly concentrating on research released between 2014 and 2024. The methodology includes guidelines for selecting studies, data origins, and the method employed to examine the collected literature, laying the foundation for an in-depth

examination of each aspect in the following sections. Figure 1 shows the proposed structure to be followed for this study.

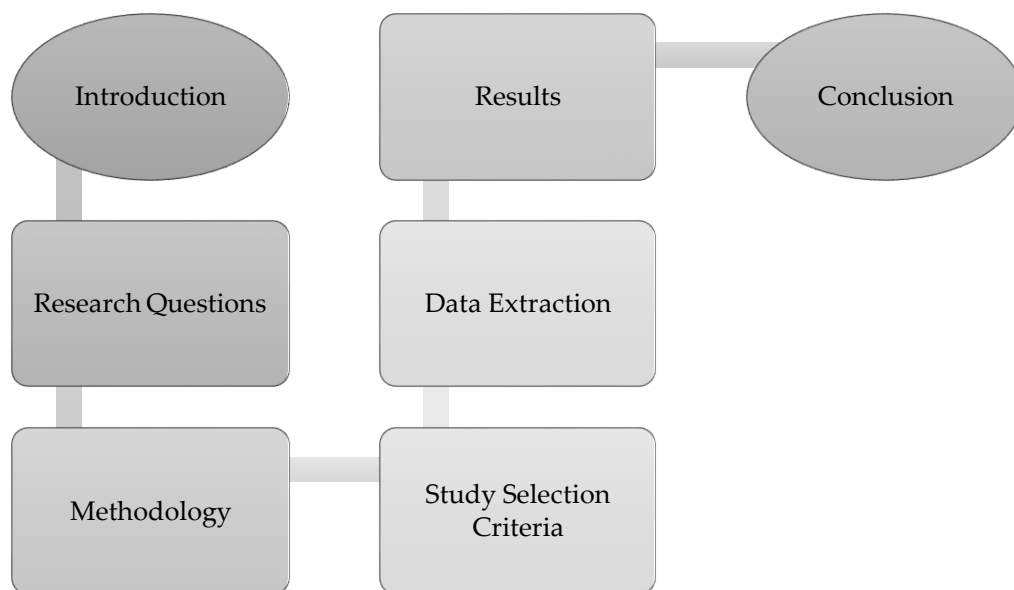


Figure 1. SLR flow diagram.

2.1. Eligibility Criteria

A thorough examination was conducted on all research papers that have been peer-reviewed and published that are relevant to studying how Big Data affect the performance of small and medium-sized enterprises (SMEs). The analysis specifically focused on research articles in English that delve into the impact of data on SME performance between 2014 and 2024. The time frame (2014–2024) was chosen to capture the most recent advancements in Big Data technologies and their impact on SMEs, as this period reflects the rapid growth in data-driven approaches in business. Only English-language articles were considered due to accessibility and to ensure consistency in the interpretation of findings. Firm inclusion and exclusion criteria were used to select research papers that emphasize the influence of data on SME performance while excluding studies unrelated to this topic. Only peer-reviewed research addressing the aspects of how data impact SME performance was considered for this review. Table 2 outlines the inclusion and exclusion criteria for this study.

Table 2. Proposed inclusion and exclusion criteria.

Criteria	Inclusion	Exclusion
Topic	Articles must focus on the impact of Big Data on SME performance.	Articles unrelated to the impact of Big Data on SME performance.
Research Framework	The articles must comprise a research framework for the impact of Big Data on SME performance.	Articles with inadequate research framework focusing on the impact of Big Data on SME performance.
Language	Papers written in English.	Papers not written in English.
Publication Period	Publications between 2014 and 2024.	Publications outside 2014 and 2024.

The literature was retrieved from major academic databases, i.e., Scopus, Web of Science, or Google Scholar, to ensure comprehensive coverage of relevant studies. To ensure the quality of the selected papers, a systematic quality assessment was carried out. Each paper was evaluated based on its methodological thoroughness, relevance to the research topic, clarity of the research framework, and the validity of its findings. The

PRISMA checklist was employed to assess the reliability of the studies. The screening process involved three authors, and any disagreements were resolved through discussion or consultation with a fourth author to enhance the accuracy of the selection process.

To ensure the accuracy of study selection and remove potential biases, a cross-checking process was conducted, where each reviewer re-evaluated the final set of studies against the inclusion and exclusion criteria. Additionally, to mitigate biases related to study origin or methodology, we ensured a diverse representation of studies across regions and research approaches. Only studies meeting the predefined quality standards were included in the final analysis to ensure the robustness of the systematic review.

2.2. Information Sources

In this analysis, the three databases that were used to conduct this systematic review are Google Scholar, Web of Science, and Scopus. These databases were chosen due to their extensive coverage of high-impact journals and peer-reviewed publications, ensuring that we captured a comprehensive view of relevant studies. We carefully reviewed a range of research papers based on their study specifics, context, methodologies, results, and implications. In addition, the databases were tested for relevance and completeness by running initial searches to ensure the research scope was adequately covered. These references were also used to explore related published materials such as conference papers, journal articles, book chapters, dissertations, and theses.

2.3. Search Strategy

Figure 2 below shows the step-by-step approach to carrying out a systematic review, starting with formulating research questions. These questions help in choosing a research methodology, encompassing a systematic literature review (SLR), planning, establishing inclusion and exclusion criteria for selecting research resources, and picking search terms. Subsequently, the procedure progresses to picking research articles through a search process and evaluation, which is crucial for ensuring high-quality references. The subsequent phase includes extracting data from the chosen research articles while concentrating on evaluating data integrity.

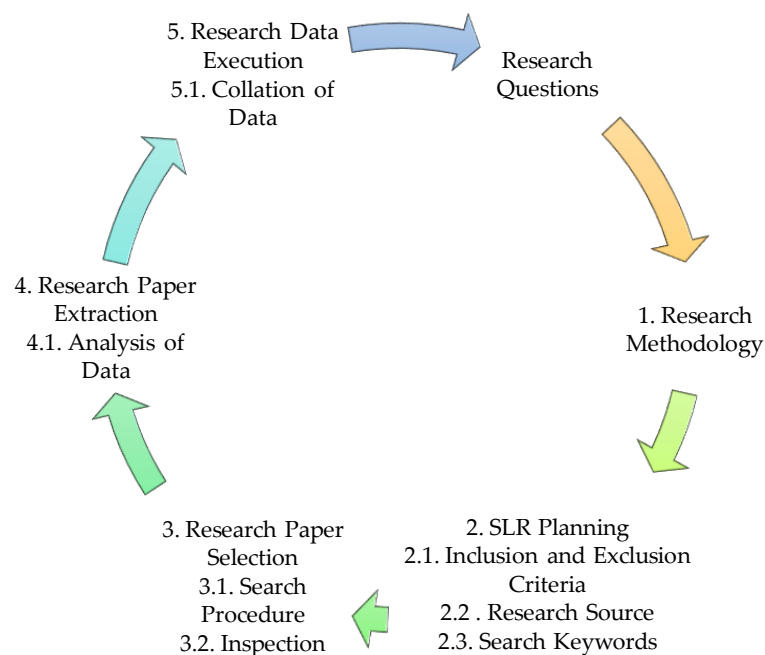


Figure 2. Procedures and stages of the review.

To ensure the completeness of the search strings, multiple rounds of searches were conducted to verify that the keywords and logical operators (“AND,” “OR”) captured all relevant studies aligned with the research questions. The search strategy presented in Table 3 utilized the logical operators “AND” and “OR” to identify pertinent studies. The search strings were reviewed, and pilot tests were conducted to confirm that they encompassed the breadth of research related to Big Data and SME performance. The search strings used for this research were (“Big Data” OR “data analytics” OR “data mining”) AND (“SMEs” OR “small and medium enterprises” OR “small and medium-sized businesses” OR “small and medium-sized enterprises”) AND (“performance” OR “Business Performance” OR “Organizational Performance” OR “Operational Performance” OR “financial performance”) AND (“impact” OR “effect” OR “influence” OR “role”). These search strings were validated by comparing the results with known key papers in the field, ensuring that all relevant studies were included. The bibliometric analysis in Figure 3 visually depicts the relationships between key terms. Network visualization highlights strong connections between central terms like Big Data analytics, SMEs, and firm performance, while the overlay visualization shows the increasing relevance of emerging topics such as innovation and green innovation. Finally, the density visualization underscores the intensity of research focus in areas such as Big Data analytics and SME performance, confirming the robustness of the search strategy.

Table 3. Search terms used in SLR.

Search Terms ¹			Databases	Fields				
Big Data OR Data Analytics OR Data Mining	AND	SMEs OR Small and Medium Enterprises OR Small and Medium-sized Businesses	AND	Performance OR Business Performance AND OR Organi- zational Perfor- mance	AND	Impact OR Effect OR Influence OR Role	Google Scholar Web of Science Scopus	Title, Abstract Key- words

¹ These terms were used only when the search for “Big Data” AND “SME performance” did not produce the expected results.

2.4. Selection Process

To ensure a relevant collection of papers for this review on the impact of Big Data on SME performance, a strict selection process was put in place. Reviewers followed a procedure to choose papers for the review. They utilized a search code with keywords like “Big Data,” “data analytics,” and “data mining,” along with terms related to SMEs, performance and impact. Each reviewer was assigned a database—Web of Science, Scopus, or Google Scholar—to gather research papers. Initially, each reviewer gathered 104 papers, which were then screened based on inclusion criteria: relevance to the topic, presence of a research framework addressing the impact of Big Data on SME performance, publication in English, and publication dates ranging from 2014 to 2024. Exclusion criteria were also applied to sort studies. The chosen papers were documented in an Excel spreadsheet for assessment. A secondary review was conducted by reviewers to confirm adherence to the inclusion criteria and address any inconsistencies by removing papers as necessary to maintain the accuracy and relevance of the data.

2.5. Data Collection Process

This section outlines the data collection process, as illustrated in Figure 4, detailing the involvement of reviewers, methods of information acquisition, and confirmation from study researchers, as well as the online database tools used. The process adhered to

systematic review best practices, particularly with the use of multiple databases to ensure comprehensive coverage of the relevant literature as presented in selected studies [45–137].

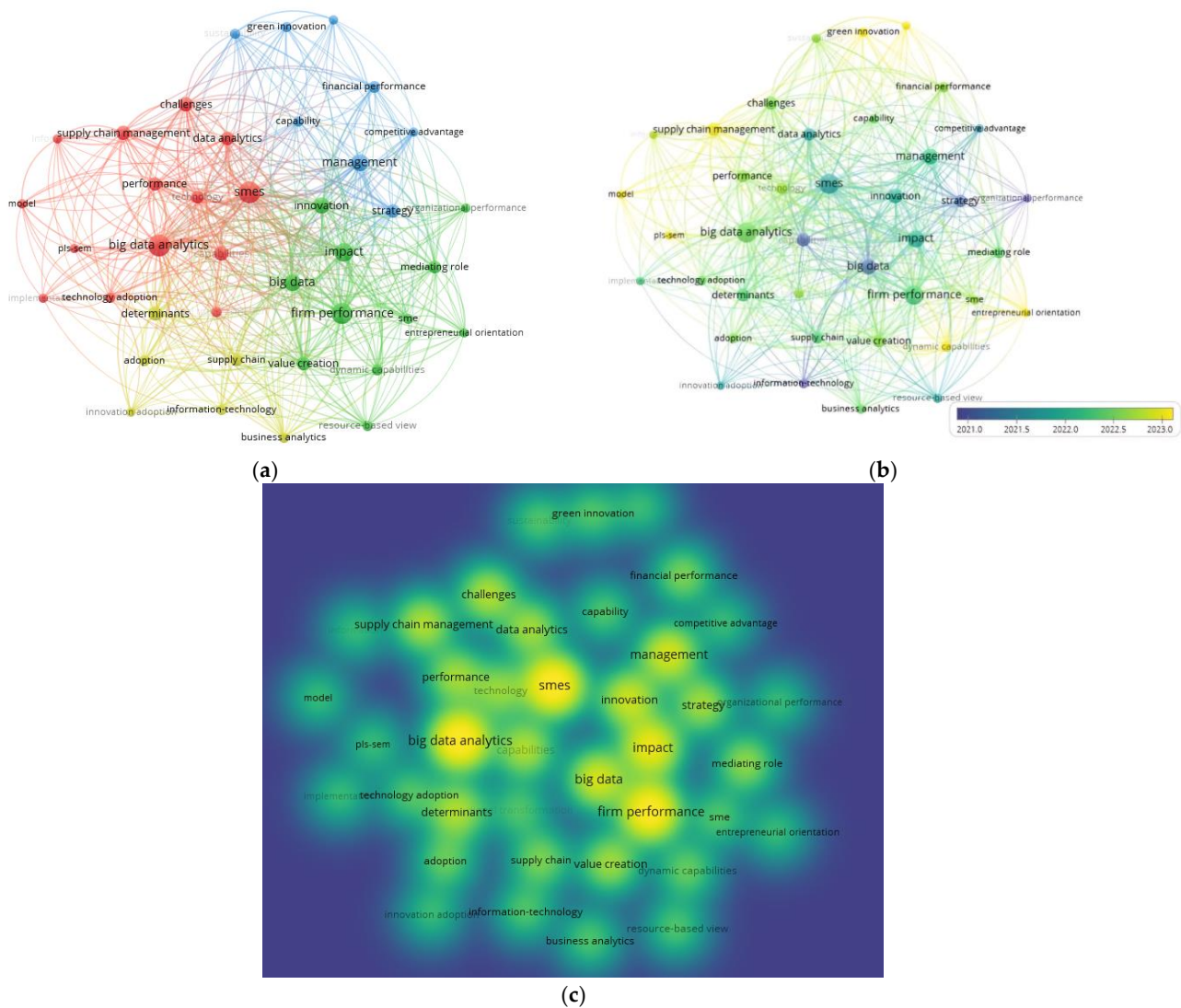


Figure 3. Bibliometric analysis of study search keywords. (a) Network visualization. (b) Overlay visualization. (c) Density visualization.

For this study, we gathered data from the University of Johannesburg (UJ) library database, using Web of Science and Scopus as primary platforms [138–150]. These databases were selected due to their extensive coverage and their recognized role in systematic reviews and bibliometric analyses. We focused on English-language studies published between 2014 and 2024, covering journal articles, conference proceedings, book chapters, theses, and dissertations. This broad selection was aimed at capturing both foundational and emerging research, ensuring a robust representation of the literature. Our refined search criteria identified 233 studies from Web of Science and 13 from Scopus, forming the foundation of the analysis [151].

To streamline the data collection process and prevent duplication, we divided the studies chronologically among three authors. One author was responsible for collecting data from studies published between 2014 and 2016, the second author handled studies from 2017 to 2020, and the third focused on studies from 2021 to 2024. Each author independently collected and contributed data to a shared online Excel document, ensuring real-time collaboration and updates. After the initial data entry, all authors jointly reviewed the Excel document to ensure

the accuracy of the collected data. Any inconsistencies, such as the misidentification of paper types, were resolved by cross-referencing the original sources.

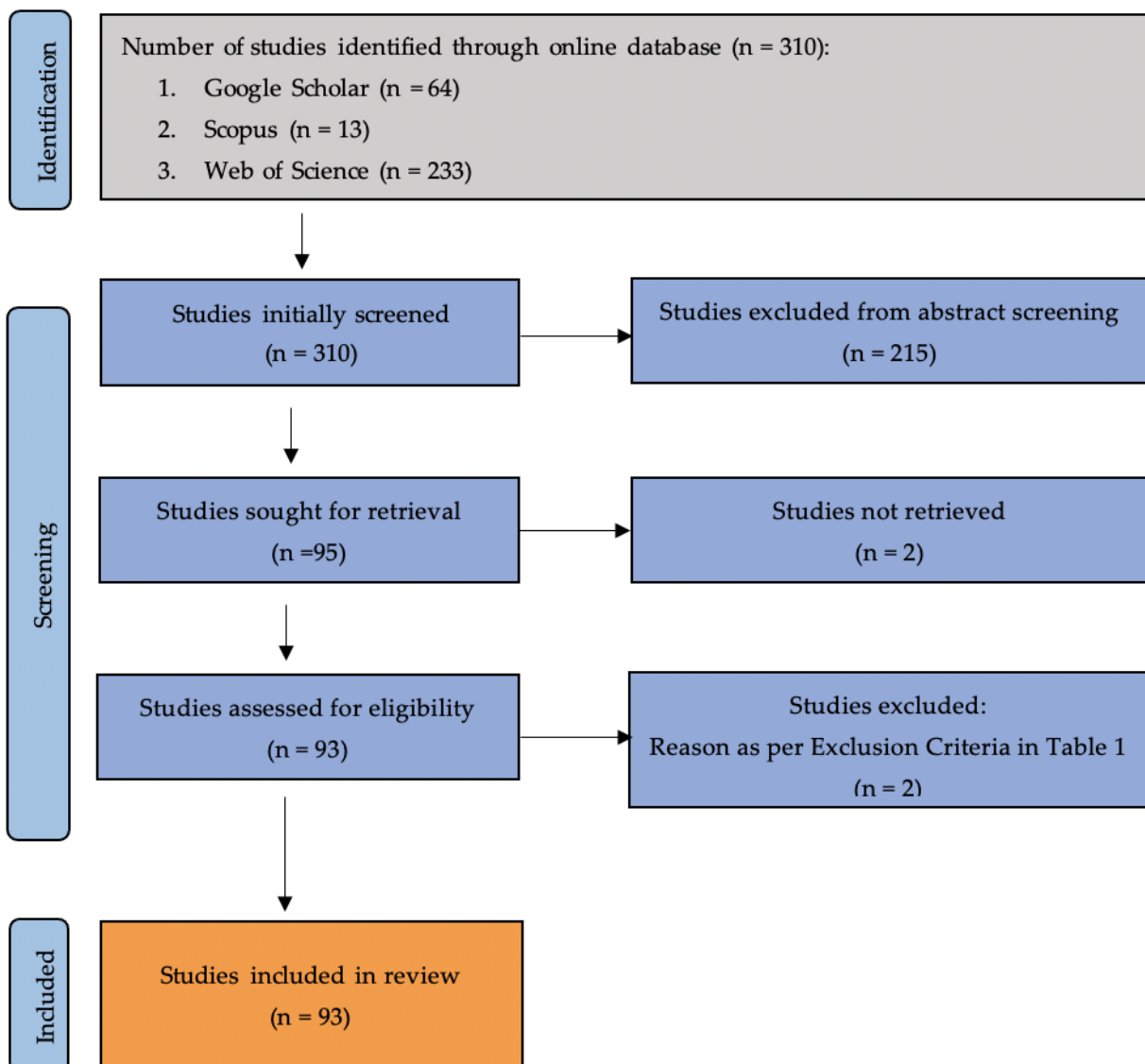


Figure 4. Data collection process flowchart.

Throughout the process, we conducted thorough cross-checks to maintain data accuracy, focusing on verifying study metadata, citations, and keywords. Each reviewer validated their assigned papers, and any discrepancies were addressed by re-examining the original documents. To mitigate biases, we implemented a balanced keyword strategy that ensured the selection of studies from diverse regions, industries, and methodological approaches. This approach ensured that the final dataset reflected a wide range of perspectives, essential for a comprehensive analysis.

In addition to the primary databases, we utilized Google Scholar to broaden our search. Google Scholar was particularly useful for capturing studies not indexed by Web of Science or Scopus. We selected 64 papers from Google Scholar based on a review of abstracts, introductions, and keywords, which were cross-checked against our research focus. Although Google Scholar does not provide an automated extraction feature like Web of Science or Scopus, the manual selection of studies was conducted carefully to align with the principles of systematic review and bibliometric analysis. Citation counts were considered a measure of influence and credibility, further guiding the selection process.

2.6. Data Items

In this systematic literature review, the focus was on gathering information that delves into the effects of Big Data on small and medium-sized enterprises (SMEs). The outcomes are grouped according to research questions to ensure a grasp of the topic.

2.6.1. Results and Data Collection

The results of this study focus on several key outcomes that demonstrate how SMEs can leverage Big Data to improve performance. These outcomes include increased profits, enhanced operational efficiency, improved customer satisfaction, and expanded market presence. These findings highlight how Big Data can facilitate data-driven decision-making, promote innovation, and provide a competitive advantage for SMEs. During the investigation, several critical factors were identified that impact the integration of Big Data within SMEs. These factors included the presence of skilled personnel, solid technological infrastructure, leadership support, financial resources, high-quality data, and organizational readiness. Understanding these elements is crucial in determining the necessary conditions for successful Big Data adoption. Desired outcomes related to this integration included increased employee productivity, the adoption of data-driven practices, optimized processes, more effective resource allocation, and an enhanced competitive edge. These results demonstrate how familiarity with and a deep understanding of Big Data can significantly boost productivity levels in SMEs. Additional outcomes sought in the analysis included improved data usability, accessibility, and accuracy, along with potential risks such as data mishandling or misinterpretation. Enhancements in interaction and increased adherence to data management protocols were also noted, reflecting the positive effects of modifying data structures within the context of data examination. Lastly, this study highlights the challenges SMEs face when implementing Big Data. These challenges include high setup costs, staffing shortages, concerns about data privacy, technological barriers, reluctance to change, issues with data accuracy, and limitations in scaling operations. These findings underscore the obstacles that could hinder SMEs from fully embracing and integrating Big Data into their operations. The relationship between Big Data and SME performance was explored in multiple studies, each employing different methodologies and yielding diverse results. Several studies employed quantitative methods, including surveys and structural equation modeling (SEM), to evaluate how Big Data influence various dimensions of firm performance, such as operational efficiency and sustainability. These studies analyzed performance by collecting survey data and utilizing advanced statistical tools.

Similarly, other studies employed quantitative analysis techniques to assess Big Data's impact on marketing strategies, resource management, and other performance metrics. These studies followed data extraction and analysis processes, utilizing data-driven insights to produce actionable conclusions for SMEs. These studies employed approaches to extract insights from the gathered data following the process in Figure 5 [151].

The listed principal elements were employed in assessing the effect of Big Data on the performance of SME systems. The figure gives the most important elements, their techniques and results that determine the efficiency of Big Data usage in the said enterprises.

2.6.2. Contributor Characteristics

This section outlines the general characteristics of the contributors to the research studies, focusing on key variables such as study design, research techniques, and other relevant aspects. Table 4 provides a detailed overview of the year of publication, the databases used, and the types of publications reviewed. The objective here is to define and describe the key variables across the evaluated studies. Several studies utilized a combination of quantitative methods, such as case studies and time-lagged designs, to explore the relationship between digital-related capabilities and outcomes like financial performance, environmental impact, and competitive advantage. These studies examined how technological advancements and environmental initiatives influence both financial and environmental outcomes in SMEs. Additionally, some investigations focused on

sustainability, employing methods like least squares structural equation modeling (SEM) to analyze the impact of Big Data on supply chain management and corporate performance. These studies often emphasized sustainable practices, aligning with circular economy principles, and highlighted the role of technologies like blockchain in driving sustainable development within SMEs [151].

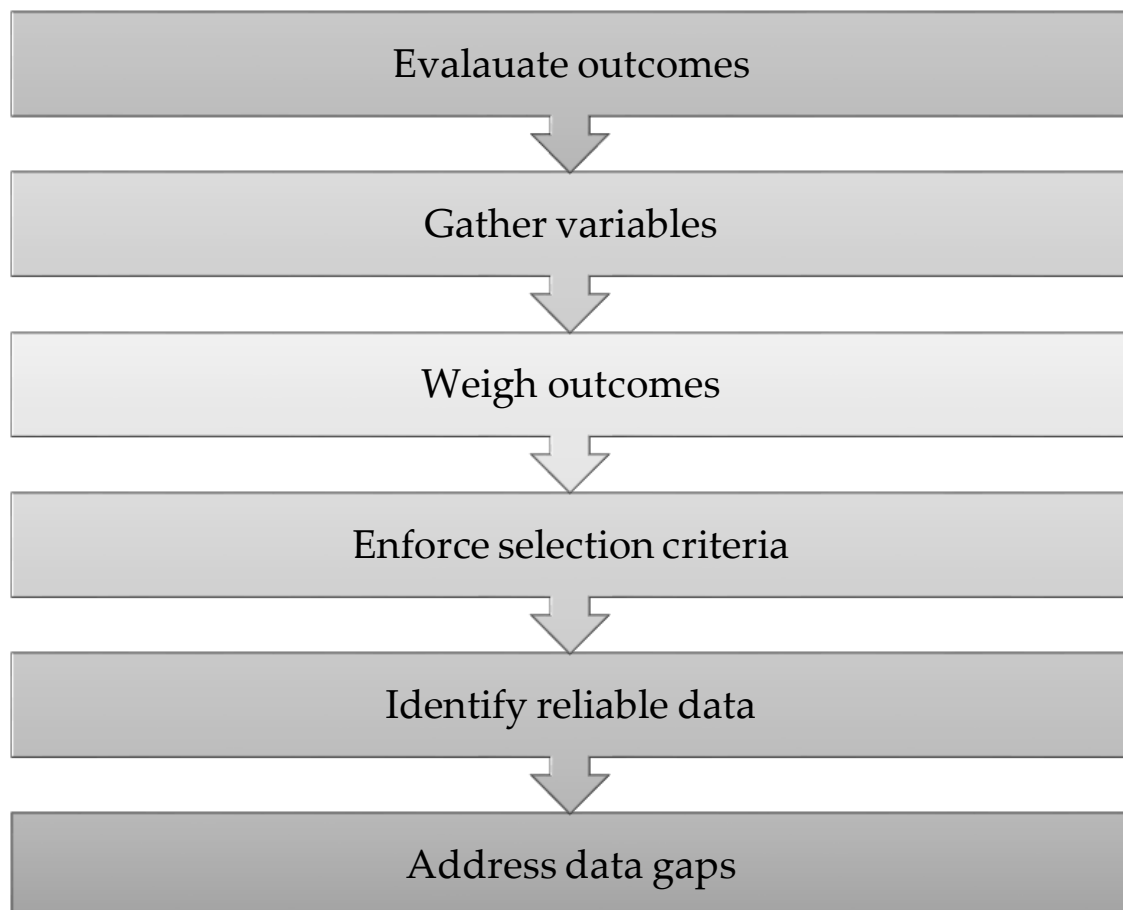


Figure 5. Initiated data item process.

2.7. Study Risk of Bias Assessment

During our review, we investigated the potential for bias by examining the quality of the studies based on the criteria for our research topic. Three reviewers conducted this assessment. Each reviewer independently analyzed the studies for objectivity, as shown in Table 5 below, followed by a discussion to reach a consensus on the bias risk for each study. No automated tools or software were involved in this assessment process. We manually reviewed the methodologies and results of each study. Bias risk was determined based on factors such as study design relevance, sample size, and data collection methods. Studies with transparent methodologies were considered to have bias risks. We also inspected any conflicts of interest or funding sources that could impact study outcomes, giving preference to studies that openly disclosed conflicts [151].

We also assessed consistency in findings within and across studies, noting any differences or unusual results. This method aimed to ensure high-quality studies in our review while identifying and addressing biases effectively.

Table 4. Summary of contributor characteristics and key variables in evaluated studies.

Fields	Description	Selections
Title	The name of the research article or paper.	None
Year	The publication year of the study.	None
Online database	The database where the article was sourced.	Google Scholar, Scopus, Web of Science
Journal name	Represents data as slices of a whole, ideal for showing proportional or percentage distribution of categories.	None
Research type	Shows parts of a whole, allowing multiple variables to be represented in the same category for easier comparison.	Article journal, conference paper, book chapter, dissertation, thesis
Discipline or subject area	Uses color coding to represent data intensity or frequency, useful for spotting patterns in large datasets.	Big Data, SME performance, business analytics
Industry context	The industry or sector the research is focused on.	SMEs, startups, small businesses
Geographic location	The region or country where the study was conducted or focused.	None
Economic context	The economic environment of the study.	Developed, developing
Types of Big Data technologies	The specific Big Data technologies used in the research.	Hadoop, Spark, NoSQL databases
Big Data analytics techniques	The analytical methods employed.	Machine learning, data mining, predictive analytics
Technology providers	Companies or organizations providing the technology.	Cloudera, Hortonworks, IBM, AWS
Technology implementation model	The mode of technology deployment.	On-premises, cloud-based, hybrid
Research design	The design of the study.	Experimental, quasi-experimental, case study, survey
Type of study	The methodology used.	Qualitative, quantitative, and mixed methods
Sample size	The number of participants or entities involved in the study.	None
Sample characteristics	Demographic or specific features of the sample.	SMEs, Big Data, IT professionals
Data collection methods	Techniques used to gather data.	Interviews, surveys, observations, document analysis
Big Data techniques	Methods used to analyze the data.	Statistical analysis, thematic analysis
IT performance metrics	Measures related to technological performance.	Data processing speed, scalability, data accuracy
Business performance	Measures of business outcomes.	Operational efficiency, revenue growth, cost savings
Organizational outcomes	Results related to the organization.	Employee satisfaction, customer satisfaction
Long-term impacts	The extended effects of the study findings.	Business sustainability, competitive advantage

Table 5. Proposed risk-of-bias assessment.

Ref.	Selection (0–4 Stars)	Comparability (0–2 Stars)	Outcome/Exposure (0–3 Stars)	Total Stars	Quality Rating
[60,101,111]	★★	★	★★	5	Low
[62,66,68,82,93,98,100,107,109,126,129,135]	★★	★★	★★	6	Low-Moderate
[50,53,55,58,59,67,70,75,77,80,84,86,87,95, 106,110,116,118,119,121,123,124,129,135]	★★★	★★	★★	7	Moderate
[45,47,48,52,54,56,57,61,63,64,69,71,74,80, 85,87,88,93,96,97,104,106,109,113]	★★★★	★★	★★★★	8	Moderate-High
[46,49,51,65,72,73,76,78,81,83,92,94,99,102, 104,108,115,117,124,130]	★★★★★	★★	★★★★	9	High

2.8. Effect Measures

In the systematic literature review of existing literature, a range of methods were utilized to evaluate the effects of Big Data on different outcomes. For increased profitability, operational efficiency, customer satisfaction, and market share, the primary effect measures included mean difference, statistical significance of correlations, or regression coefficients. When analyzing the factors affecting data implementation, correlation coefficients and statistical significance in regression models were key indicators. Assessing areas like enhanced employee productivity, data-driven practices, process optimization, resource allocation, and competitive advantage involved measures like difference and percentage change from tests. Furthermore, aspects like data usability, accuracy, risks of data loss, communication effectiveness, and compliance adherence were evaluated using metrics such as risk ratios and compliance rates. Challenges in adopting Big Data, such as cost implications or the need for personnel, were measured through the frequency of events and percentage impacts. In studies mentioned in the table summary section, quantitative research approaches utilizing methods like structural equation modeling (SEM) or partial least squares SEM incorporated measures such as SEM results, factor loadings, mean differences, and regression coefficients [151].

For qualitative research, such as case studies and thematic analysis, we used measures like categories, qualitative observations, and findings from case studies. Mixed-method research involves a combination of measures (such as regression coefficients and SEM results) along with insights (like thematic analysis findings). In studies that examined the effects on performance, we looked at economic performance through variations in regression coefficients and statistical significance. Operational and environmental performance was assessed by differences, effect sizes, and coefficients from structural equation modeling. Sustainability and competitive advantage were assessed using effect sizes, regression coefficients, and correlation measures.

2.9. Synthesis Methods

In compiling the research necessary for our systematic literature review about the impact of Big Data on the performance of small and medium-sized enterprises (SMEs), we took a systematic approach to identifying high-quality studies. The processes of synthesis are significant, and the general tasks are demonstrated in Figure 6. The supplemental strategies deployed in reviewing are the key components in the integrity and connection of the study's findings. Compiling the research for our systematic literature review on how Big Data affect the performance of small and medium-sized enterprises (SMEs), we took a systematic approach to ensure that we included relevant high-quality studies [151].

The eligibility criteria, preparing data for synthesis, accumulating and presenting data, and synthesizing the data were included. Furthermore, we also looked at the reasons for heterogeneity in study results and carried out a sensitivity analysis to test the robustness of our synthesized results.

2.9.1. Study Eligibility Criteria

We compared the characteristics of studies focusing on how they aligned with our key themes and findings concerning Big Data and SMEs. Our selection criteria prioritized papers that directly related to our topic and those with several citations. We carefully examined abstracts to comprehend each study's objectives and methodologies. We specifically looked for studies that explored the impact of data on SMEs using mixed methods. To ensure the credibility of our sources, we excluded literature reviews and included only peer-reviewed papers from sources. By using web filters, we avoided publications guaranteeing that the studies in our review were trustworthy and authoritative. The studies selected for review ranged from 2014 to 2024 and encompassed articles, journals, conference papers, theses, and dissertations. Each paper underwent peer review to meet our quality standards, while literature reviews were excluded to maintain the integrity of our review [151].

2.9.2. Data Preparation for Synthesis

To ensure the data were ready for presentation and analysis, we followed a series of steps to ensure accuracy and consistency. Initially, we worked together to go through our Excel dataset focusing on the names of authors and paper titles to identify and remove any duplicate entries. We used Excel's "Remove Duplicates" function to eliminate rows while considering situations where the same article might have been listed with titles by the same author. For records with missing data that could not be reliably estimated due to inaccuracies, we decided to exclude those articles from our analysis. In cases where data were missing, we labeled them as "Not Specified" rather than "Not Applicable" to accurately represent the gaps. We also standardized all data entries for consistency by converting text formats into formats as needed and ensuring the same formatting for all data entries [151].

2.9.3. Data Visualization and Tabulation Methods

To visualize patterns and detect inconsistencies, we created pivot tables. These tables helped us easily identify any differences, such as variations in how journal articles were classified. By creating representations like line charts, bar graphs, and other charts mentioned in Table 6, we could track the research distribution over time and prevent errors that may occur during manual review, ultimately improving the quality and dependability of our data synthesis [151].

Table 6. Pivot chart to visualize and analyze data.

Chart Type	Purpose	Data Representation Format
Bar chart	Displays categorical data with rectangular bars, ideal for comparing different categories or variables in a dataset.	Numbers
Column chart	Similar to a bar chart, but with vertical bars, it is useful for comparing the frequency or number of categories.	Numbers
Line chart	Shows trends over time by connecting data points with a continuous line.	Numbers
Pie chart	Represents data as slices of a whole, ideal for showing proportional or percentage distribution of categories.	Percentages (%)
Stacked bar chart	Shows parts of a whole, allowing multiple variables to be represented in the same category for easier comparison.	Numbers and Percentages (%)
Scatterplot	Plots individual data points on an X and Y axes to explore relationships or correlations between two variables.	Numbers

2.9.4. Synthesis Methodology

A systematic approach was used to synthesize the study findings, utilizing a set of criteria organized in an Excel spreadsheet. This structured method helped in comparing and analyzing aspects of the studies included, focusing on variables like the title, publication year, and source databases (Google Scholar, Scopus, and Web of Science), with their respective number of studies found, represented in Table 7. The studies were grouped by journal name, research type (article journal, conference paper, book chapter, dissertation/theses), and citation count [151].

Table 7. Results obtained from literature search.

No.	Online Repository	Number of Results
1	Google Scholar	64
2	Web of Science	233
3	Scopus	13
Total		315

2.9.5. Exploration of Heterogeneity Causes

The synthesis was enhanced by considering the field or subject area specifically related to data analytic techniques for small and medium-sized enterprise (SME) performance. Factors like industry context (SMEs, startups) and geographical location played roles in distinguishing studies based on the landscape (developed versus developing countries). Further categorization involved examining types of data technologies employed as indicated in Table 8 (Hadoop, Spark, NoSQL databases) and analytic techniques utilized (machine learning, data mining, predictive analytics) [151].

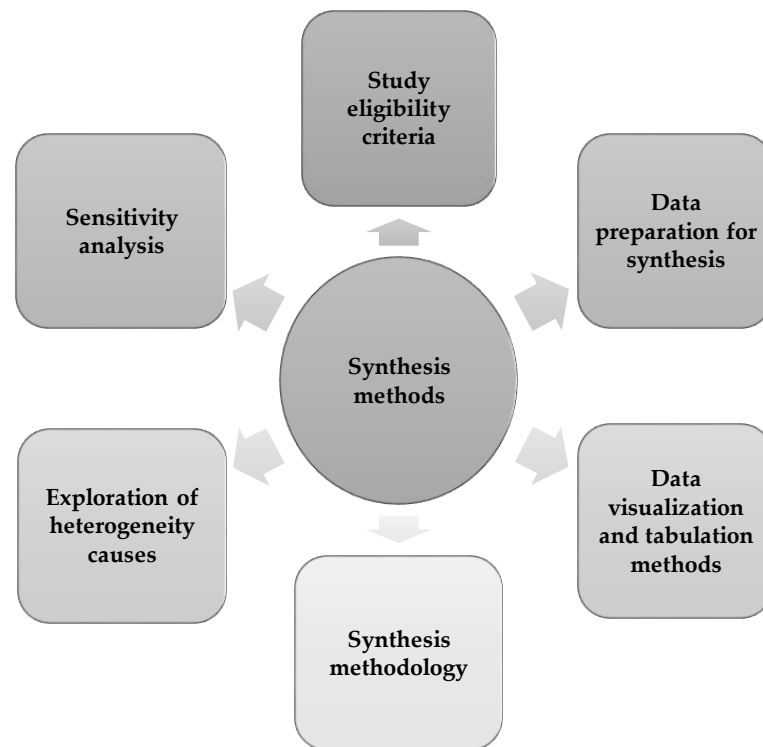


Figure 6. Synthesis methods.

Table 8. Types of Big Data technologies.

Types	Description
Hadoop	A framework developers can use for managing very large datasets in a distributed environment using simple programming models that span multiple clusters. It enables the expansion of additional machines in addition to the storage servers to a hundred thousand with a local processing unit and a local disk.
Spark	An analytics system that can process an entire Big Data stack in one tool that includes stream processing, SQL, machine learning, and graph computation processing engine. A particular processing framework that brings data into memory and processes it there instead of inputting data from a disk every single time; therefore, it is appropriate for real-time analysis of data.
NoSQL Databases	This approach of database management systems is suitable for systems that require support for a variety of data formats such as relational, document, column-oriented, and graph databases. NoSQL databases are built with specific principles in mind, and they are most efficiently used in a Big Data environment with a great deal of data that are advancing in complexity.

2.9.6. Sensitivity Analysis

Moreover, the study also reviewed the technology providers mentioned (Cloudera, Hortonworks, IBM, AWS) and different technology implementation models (on-premises cloud-based hybrid). The study’s structure, research approach (whether quantitative, qualitative, or mixed methods), sample size, and sample characteristics were examined to explore the variety of methodologies used in the research. The methods of gathering data (interviews, surveys, observations, document reviews) and analyzing data (analysis, thematic analysis) were reviewed to understand how each study handled and interpreted the information.

To bring together the findings, we thoroughly examined aspects such as IT performance metrics (like data processing speed, scalability, and data accuracy), business performance metrics (including efficiency, revenue growth, and cost savings), organizational impacts (such as employee satisfaction and customer satisfaction), and long-term effects

(such as business sustainability and competitive advantage). This method allowed us to identify patterns and trends from the studies, leading to an analysis of the data.

This approach effectively considered a range of studies. It laid a strong groundwork for combining the results. By categorizing studies based on criteria, we were able to assess the presence and level of statistical diversity. Differences in research design, sample sizes, data collection methods, and the utilization of Big Data technologies and analytical techniques indicated varying degrees of statistical diversity. This evaluation guided our synthesis process by considering differences in study outcomes and enabling us to reach conclusions [151].

2.10. Reporting Bias Assessment

In our analysis, we carefully considered the potential for reporting bias, where certain outcomes are selectively shared while others are omitted. Such bias can skew conclusions, making certain effects appear stronger or more consistent than they may be. To address this, we reviewed the methodology and results sections of each study to ensure the outcomes aligned with the original research objectives. We assessed whether all relevant findings were reported, noting instances where data appeared incomplete or missing, and considering how this could impact the overall analysis. We also accounted for the possibility of publication bias, where studies with favorable outcomes are more likely to be published compared to those with neutral or negative results. To mitigate this risk, we included a diverse range of studies from various sources and contexts, ensuring a more comprehensive representation of the evidence.

Table 5 summarizes the overall quality of each study, categorized by selection, comparability, and outcome/exposure. The outcome/exposure category was particularly important for assessing reporting bias, as it evaluates how thoroughly a study reported its findings. Studies that demonstrated greater transparency in reporting received higher ratings, while those that omitted key information were rated lower. By cross-referencing these ratings in Table 5, we accounted for reporting bias in our overall assessment. Studies with lower ratings in this area were examined more closely to determine if their conclusions were affected by incomplete reporting. This approach allowed us to present a more balanced and accurate summary of the evidence [151].

2.11. Certainty Assessment

This section outlines the approach used to evaluate the reliability of the evidence gathered concerning Big Data's impact on SME performance, ensuring the findings were both credible and robust. The literature reviewed was systematically analyzed using a set of five quality assessment (QA) criteria, as outlined in Table 9. These criteria were selected to assess the dependability, relevance, and overall quality of the studies, forming a solid basis for the conclusions drawn in this research. This evaluation process was essential to determine the strength of the evidence and ensure that the findings accurately reflect how Big Data influence various aspects of SME performance, including business growth, operational efficiency, and financial outcomes.

Table 9. Research quality question results.

Questions(Q)	Research Quality Questions
Q1	Are the research objectives explicitly outlined and well defined?
Q2	Is the research methodology comprehensively detailed?
Q3	Is the impact of Big Data on SME performance thoroughly and clearly analyzed?
Q4	Are the methods of data collection comprehensively detailed and appropriate?
Q5	Do the research findings add to the existing literature on the topic?

The quality assessment (QA) questions were rated on a scale from zero (0) to one (1). A score of 0 was assigned for a "no" response, 0.5 given when the criteria were "partially" met, and a score of 1 was awarded for a "yes" response. This rating system was uniformly

applied to all five questions (Q). As a result, each piece of literature being reviewed could achieve a total score of up to 5 points. The outcomes of the quality assessment for the literature reviewed are detailed in Table 10.

Table 10. Findings from the literature quality assessment.

Ref.	Q1	Q2	Q3	Q4	Q5	Total	%
[45,46,49,51–53,56–58,61,64,65,71–75,77,80,82,84,85,87,90,107,123,125,127,128,133]	1	1	1	1	1	5	100%
[47,48,55,59,60,77,79,104,111,112,125,127,129,132]	1	1	0.5	1	1	4.5	90%
[54,63,80,92,95–103,105,109,124,134,137]	1	0.5	0.5	1	1	4	80%
[69,70,86,87,89,90,113,114,137,141]	1	0.5	0.5	0.5	1	3.5	70%
[50,62,66,68,85,94,106,113–123]	1	0.5	0.5	0	1	3	60%
[67,82]	1	0.5	0	0	1	2.5	50%

This table shows the quality assessment scores for each paper based on five criteria related to the impact of Big Data on SME performance. Higher scores indicate better quality and relevance.

3. Results

Figure 7 outlines the essential components that influence the results, such as study selection, study characteristics, and the risk of bias, all of which play a crucial role in shaping the reliability of the findings. Additionally, it highlights the importance of synthesizing individual study results, which is key to forming comprehensive conclusions. The figure also emphasizes the significance of considering reporting biases and assessing the certainty of evidence to ensure that the presented results are both accurate and dependable. Each of these factors is critical in interpreting the overall findings, offering a clearer view of the data.

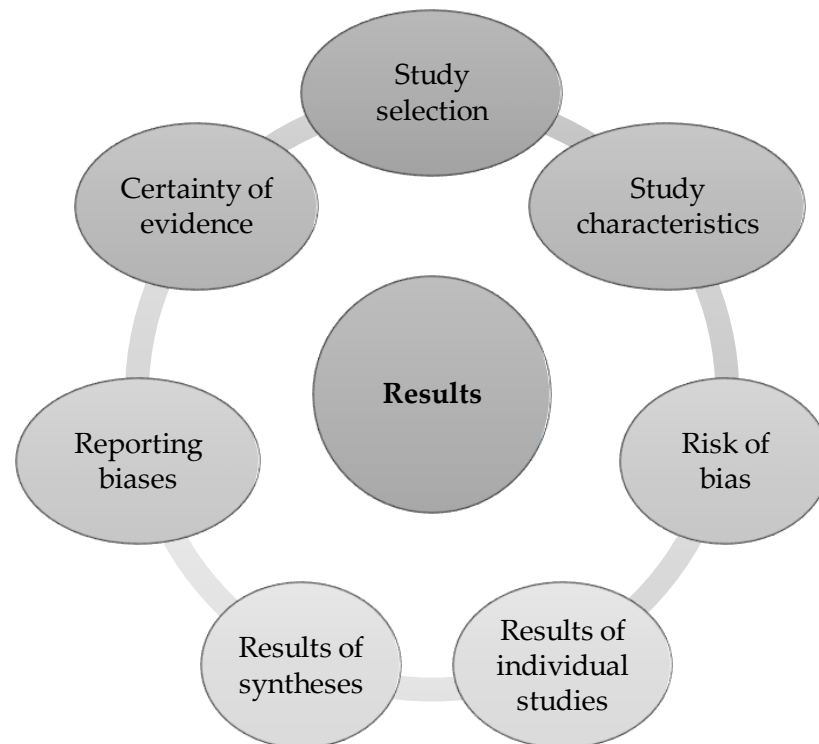


Figure 7. Key phases in evaluating systematic review results.

3.1. Study Selection

The selection process for research papers is outlined in Figure 8. A total of 93 papers were chosen from three major databases, with their distribution presented as percentages. Most of the papers (63.44%) were sourced from Web of Science, followed by 22.58% from Google Scholar and 13.98% from Scopus. These papers were selected based on specific

inclusion and exclusion criteria to ensure that only the most relevant studies were included in the final analysis of this review.

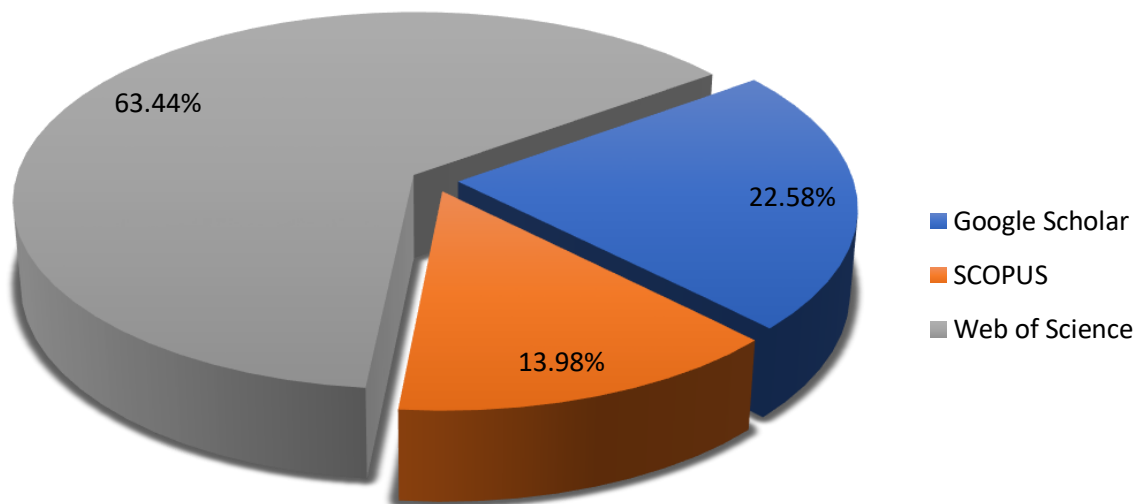


Figure 8. Distribution of online data sources.

The literature review revealed that small and medium-sized enterprises (SMEs) encounter significant challenges in leveraging Big Data capabilities. The primary barriers include resource constraints, limited data expertise, and a lack of organizational readiness. These factors hinder SMEs' efforts to improve decision-making, operational efficiency, and competitive advantage. Several studies emphasize the importance of technological infrastructure and employee skills in overcoming these challenges. Financial limitations often restrict SMEs from investing in advanced analytics tools, while gaps in data literacy impede effective data utilization. Additionally, the absence of a clear strategic vision for data collection and analysis leads to the underutilization of valuable insights, perpetuating inefficiencies and missed opportunities for innovation. These barriers prevent SMEs from fully harnessing the potential of Big Data, directly impacting their performance and market competitiveness.

The review also highlighted notable gaps in research, particularly concerning regional differences in Big Data adoption among SMEs. There is a scarcity of studies focusing on SMEs in developing regions, overlooking how diverse economic and infrastructural conditions influence data implementation. While many studies address technical and organizational barriers, fewer explore cultural factors that affect Big Data strategies, such as leadership attitudes toward innovation and risk-taking. Addressing these gaps is crucial for understanding how Big Data can effectively transform SMEs across different contexts and industries, facilitating their growth and competitiveness in an increasingly data-driven marketplace.

3.2. Study Characteristics

Figure 9 shows the research findings regarding the impact of Big Data on the performance of SMEs, illustrating a shifting level of interest between 2016 and 2024.

Table 11 provides a momentary view of the research published during this period, categorized by type of journal article and conference paper. Interestingly, no scholarly articles were available for the years 2014 and 2015, suggesting that the incorporation of data into SME operations was not a focus during those specific years. It is reasonable to assume that during that period, the utilization of data technologies was still in its early phases, with more emphasis placed on larger corporations rather than SMEs. The table highlights a steady increase in publications from 2016 through 2024, with a notable rise in journal articles.

Starting from 2016, there is evidence of a gradual rise in research attention, beginning with five publications in 2016 and steadily increasing to six in 2017. However, there was a decrease in activity in 2018, when two papers were published. This could indicate a temporary shift in research priorities or challenges faced during the early stages of implementing Big Data practices within SMEs. In 2019 and 2020, there was a rise in the number of published papers, reaching a peak of 17 in 2020. This increase may be attributed to the growing acknowledgement of how Big Data can benefit SMEs driven by the greater availability of Big Data tools and a heightened awareness of their advantages.

Table 11. Distribution of conference papers and journal articles by publication year.

Published Year	Conference Paper	Journal Article
2016	3	2
2017	2	6
2018	1	2
2019	3	7
2020	3	13
2021	1	11
2022	2	10
2023	0	15
2024	0	12

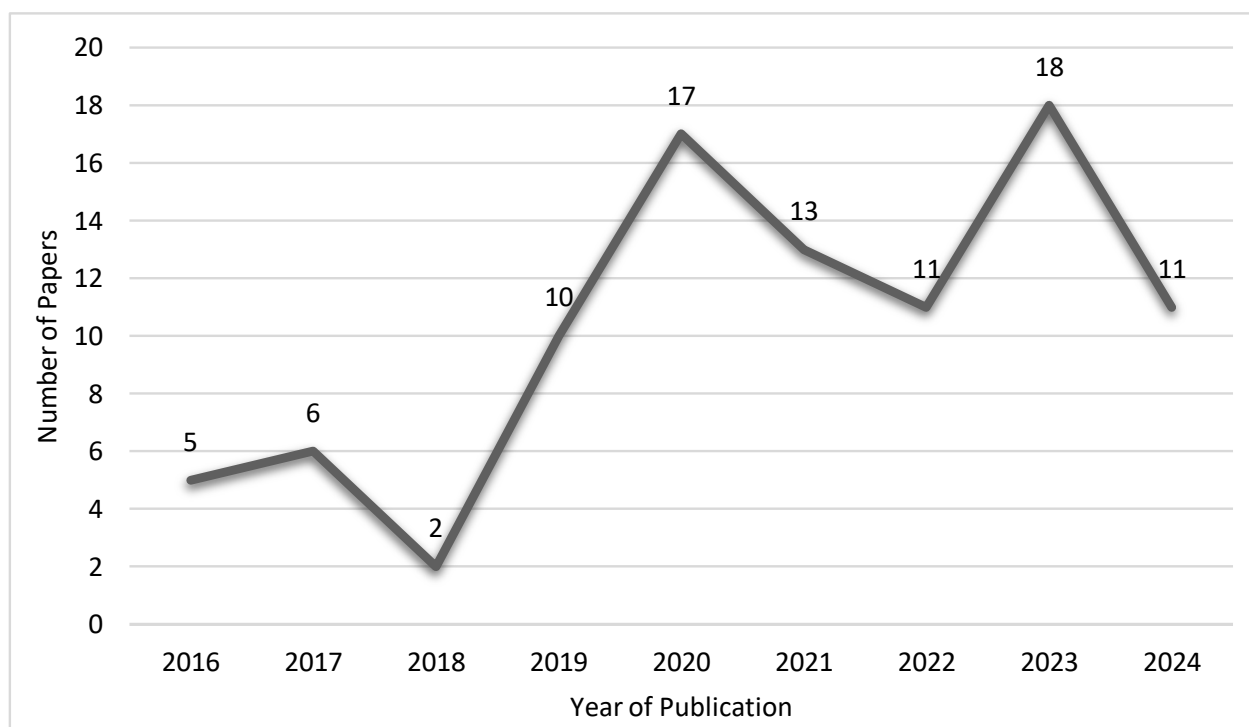


Figure 9. Annual distribution of scholarly publications (2014–2024).

Figure 10 presents the distribution of titles by country identified in this systematic literature review. The bar chart provides a detailed breakdown of the number of titles across various countries, highlighting regions with a higher concentration of research activity. Notably, China and Italy emerge as prominent contributors, suggesting focused academic and research efforts in these areas. This visualization is crucial for understanding the global landscape of the reviewed literature, offering insights into the geographic distribution and influence of research on this topic.

Table 12 outlines the broad impact of Big Data (BD) across various sectors, underscoring its critical role in improving firm performance, decision-making processes, and

innovation capabilities. It highlights how BD enhance financial performance, drives growth, and supports environmental sustainability by optimizing operational efficiency and enabling strategic decisions.

Key elements, such as organizational readiness, leadership commitment, and the integration of Industry 4.0 technologies, are essential for realizing these benefits. The table also addresses common challenges linked to BD adoption, such as financial limitations and a lack of expertise, while suggesting potential solutions like cloud-based analytics and data-driven business models. It further demonstrates how BD adoption serves as a conceptual framework for exploring innovation in resource-constrained environments, contributing to the development of new models and future research directions.

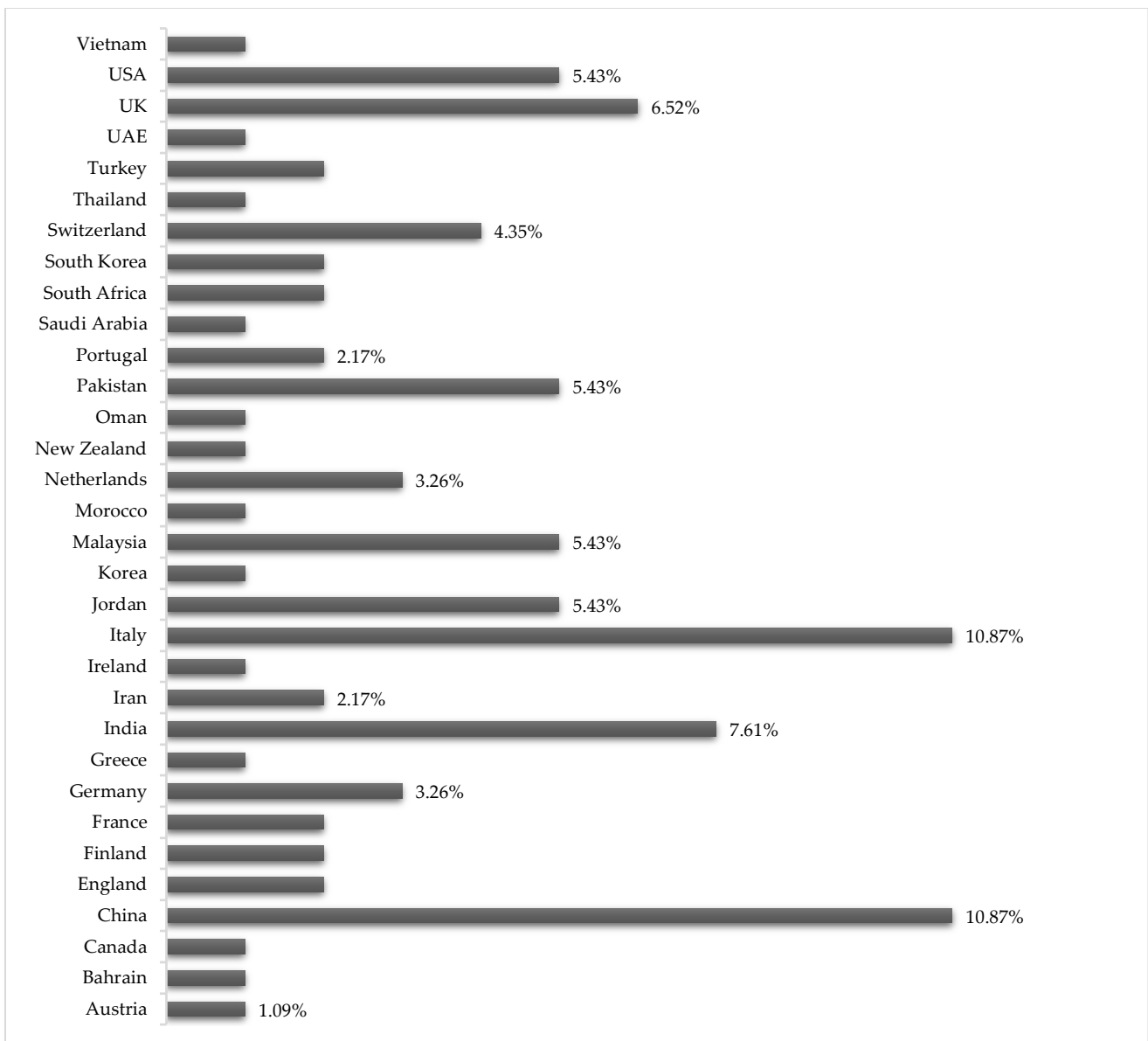


Figure 10. Countries of studies.

Table 12. Contributions of studies.

Category	Ref.	Contribution
Big Data (BD) and Firm Performance	[45,47,52,53,59,62,72,74,86,87,100,105,126,134]	BD enhance financial, growth, innovation, and environmental performance in SMEs. Key drivers include organizational readiness and top management support. Proposes a conceptual framework linking BD adoption to enhanced innovation in resource-constrained environments.
Industry 4.0 and Digital Capabilities	[46,50,55,60,63,75,78,91,95,129,133]	The adoption of Industry 4.0 technologies improves operational, financial, and innovation performance, particularly in manufacturing. Suggests a taxonomy of digital capabilities that SMEs can leverage for effective BD implementation and innovation outcomes.
BD for Decision-Making and Knowledge Management	[48,51,66,67,69,81,96,101,108,109,125]	BD enhance decision-making and knowledge management, fostering productivity. Proposes a conceptual framework integrating KM models that leverage BD for strategic advantage, addressing barriers like lack of expertise and complexity in resource-limited contexts.
BD and Competitive Advantage	[58,61,72,76,81,82,88,94,106,122]	BD improve competitive advantage through enhanced market performance and supply chain coordination. Discusses how entrepreneurial orientation and co-innovation can form a theoretical basis for understanding BD's role in resilience and competitive positioning in SMEs.
Adoption Challenges and Barriers to BD	[93,101,113,114,126,135–137]	Identifies common barriers to BD adoption such as financial constraints and lack of expertise. Suggests a comprehensive model based on the TOE framework that considers organizational readiness as a critical moderator in resource-constrained environments.
BD in Supply Chain Management	[71,75,78,87,92,98,112]	BD enhance supply chain efficiency through improved visibility and real-time adjustments. Proposes a framework connecting BD capabilities to green product development and sustainable supply chain outcomes, emphasizing the unique challenges faced by SMEs.
Cloud-Based BD and Scalability	[68,70,84,89,112,115]	Cloud computing provides scalable solutions for SMEs to access BD technologies. Introduces a research agenda on the role of cloud-based BD in overcoming scalability and security challenges in innovation for SMEs.
BD and HR Practices	[80,82]	BD improve HR service quality and innovation competency. Proposes a conceptual framework illustrating how BD can enhance HR practices, focusing on the importance of openness in change and technical skill development in SMEs.

Table 12. Cont.

Category	Ref.	Contribution
Big Data-Driven Innovation	[59,73,79,97,118,124]	BD fosters green innovation, improving economic and environmental outcomes. Suggests developing a taxonomy of data-driven business models that enhance innovation and value creation, particularly in Industry 4.0 contexts.
BD in Financial Services	[77,103,107,129]	BD supports SMEs in credit assessment and financing, reducing information asymmetry. Proposes a framework integrating financial and non-financial data for credit evaluations, particularly for SMEs with weaker financial conditions.
BD and Project Performance	[85,135]	BD positively influences project performance by mediating relationships between knowledge management, green purchasing, and operational capabilities. Suggests a model combining DEA with machine learning techniques to improve performance prediction accuracy for SMEs.
BD and Network Security	[93,99]	Security frameworks that integrate BDA enhance network reliability and data validity, addressing privacy concerns. Proposes a research agenda for developing advanced security techniques, like fog computing, tailored for SMEs to protect their BD investments.
BD in Agriculture and SMEs	[102,104]	BD affect management control systems in agricultural SMEs. Proposes a framework illustrating the interplay between leadership, managerial culture, and BD's role in stabilizing or changing management practices in resource-limited agricultural contexts.
BD and Innovation Efficiency	[131,133]	Absorptive capacity is pivotal for sustainable economic performance, influencing product innovation efficiency. Proposes a conceptual framework highlighting the mediating effects of BD capabilities in linking market development strategies to innovation efficiency.
BD in Traffic Systems	[136]	Crowdsourced traffic data enhances accuracy in traffic event detection. Suggests a theoretical framework linking BD integration with machine learning to improve urban traffic management, providing insights into cost reduction compared to conventional methods.

3.3. Risk of Bias

When examining how Big Data affect the performance of small and medium-sized enterprises (SMEs) it is crucial to grasp the approaches utilized in research studies, as these greatly impact the trustworthiness and relevance of the results. Figure 11 below displays the usage of research methods in studies on this subject, emphasizing the potential bias risks linked to each method. A variety of approaches such as case studies, surveys, and experimental designs have been utilized, each having its strengths and weaknesses when addressing inquiries about how Big Data influence SMEs.

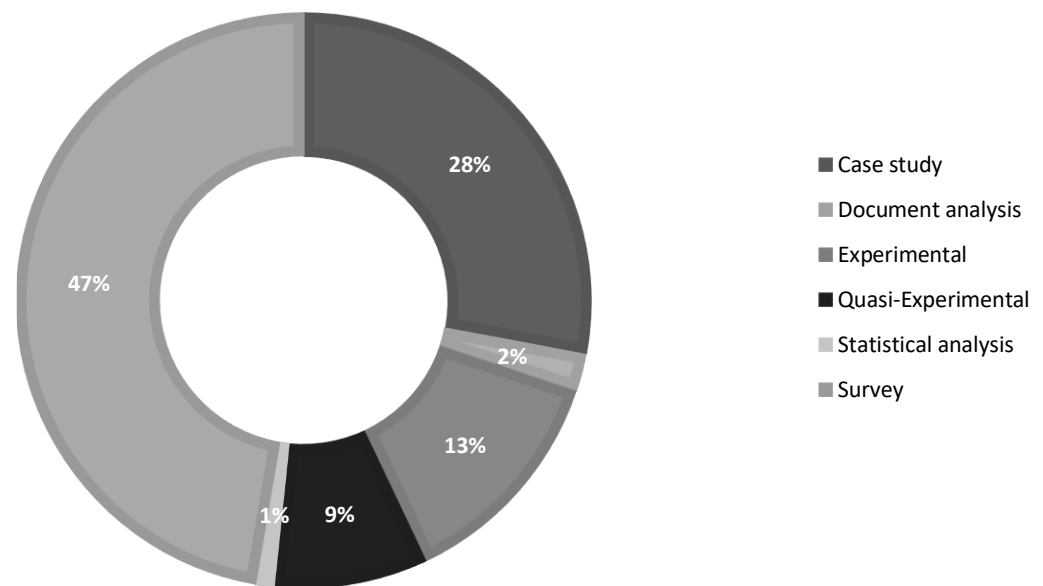


Figure 11. Distribution and implications of research designs.

Figure 11 presents the data showing that surveys are the most widely used method, representing 47% of the studies reviewed. Although surveys are efficient for gathering large datasets, they come with certain limitations, primarily the risk of self-reporting bias. Respondents may provide incomplete or inaccurate information, especially when dealing with complex topics like Big Data utilization in SMEs. Moreover, surveys often simplify the intricate dynamics of Big Data implementation, focusing on easily quantifiable outcomes without capturing the underlying complexities that shape these outcomes. This is particularly problematic in the SME context, where challenges related to Big Data adoption are often context-specific and difficult to quantify.

Case studies, accounting for 28% of the research, offer valuable in-depth insights into individual SME experiences, but face limitations in terms of generalizability. These studies focus on specific contexts, limiting broader conclusions about Big Data's influence on SME performance across various sectors and regions. Experimental and quasi-experimental designs constitute 13% and 9% of the studies, respectively. While these methods help establish causality, their controlled environments may not accurately reflect the real-world complexities SMEs face in their operations. The minimal use of quantitative methods such as meta-analysis (1%) and document analysis (2%) highlights an additional bias, which is the underrepresentation of long-term trend analyses and assessments of historical data. This imbalance limits our understanding of how Big Data influence SME performance over time, as the lack of longitudinal or cross-sectional studies prevents the identification of sustained patterns and impacts in data-driven decision-making.

The predominant reliance on surveys introduces a reporting bias that can distort overall findings in Big Data research on SMEs. Surveys tend to focus on general trends and perceptions, but may overlook complex, context-specific challenges like resource constraints, data literacy gaps, and integration difficulties. These challenges are often

better explored through qualitative methods such as case studies or interviews, which are underrepresented in the current body of research. The heavy bias toward quantitative methods risks producing a narrow and incomplete view of Big Data’s true impact on SMEs.

Emerging themes from the studies include resource constraints, where many SMEs lack the financial and human capital to invest in advanced data analytics technologies and skilled personnel. This resource scarcity significantly affects their ability to leverage Big Data for improved decision-making, innovation, and competitiveness. Another crucial gap is data literacy, as many SME employees lack the skills to interpret and act upon data insights. Inadequate integration of Big Data into existing processes and systems further leads to fragmented data sources and inefficient workflows, which limit the potential benefits of data-driven decision-making. Cultural resistance to change also impedes the adoption of data-driven practices, thereby restricting performance improvements.

These challenges are not isolated, but are intrinsically linked to SME performance outcomes. For instance, limited resources not only prevent SMEs from acquiring Big Data tools but also create a cycle of underperformance, where their inability to fully utilize data constrains growth and innovation. Similarly, insufficient data literacy can result in poor strategic decisions, eroding competitive advantage. These factors—resource limitations, data literacy gaps, and integration difficulties—directly affect operational efficiency and hinder SMEs’ ability to respond swiftly to market changes. Without adequate integration, SMEs struggle to compete in increasingly data-driven markets.

While the studies reviewed offer valuable insights, significant gaps remain. The sector-specific factors and regional disparities in data access and technology adoption are underexplored, limiting our understanding of how these variables influence Big Data challenges for SMEs. The overreliance on surveys and quantitative methods also restricts the depth of findings. Future research should adopt a mixed-method approach, incorporating both quantitative and qualitative analyses to provide a more nuanced and comprehensive understanding of how Big Data can enhance SME performance. Longitudinal studies, more qualitative research, and region-specific investigations would be particularly useful in addressing reporting biases and offering a more complete picture of Big Data’s impact on SMEs.

3.4. Results of Individual Studies

Figure 12 shows how different business performance results are seen in the context of how Big Data impact SMEs’ performance based on an analysis of 93 studies.

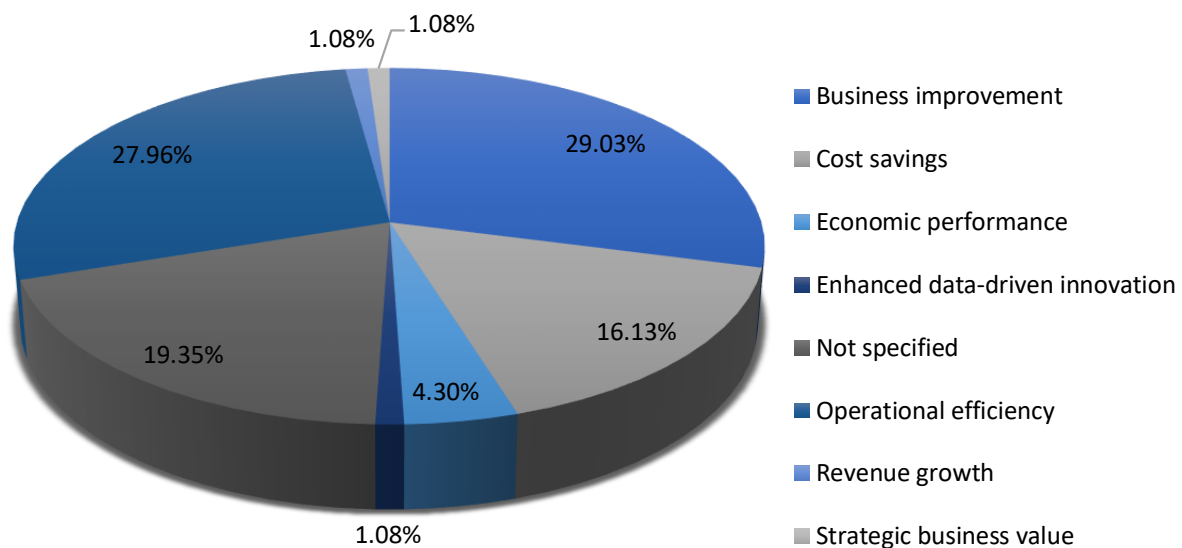


Figure 12. Distribution of business performance metrics.

As shown in Figure 12, the most common outcome observed in the studies is business improvement, accounting for 29.03%. This indicates that the integration of Big Data technologies by SMEs is predominantly linked to business enhancements, particularly through improved decision-making and better alignment with market demands. Economic performance and revenue growth are also prominent outcomes, representing 27.96% and 19.35% of the studies, respectively. The considerable percentage associated with economic performance suggests that Big Data often provide SMEs with advantages such as increased market presence and a stronger competitive edge. Revenue growth highlights the financial benefits that SMEs gain from utilizing Big Data, underscoring the impact on business prosperity.

Cost savings, which appear in 16.13% of the studies, show that while reducing costs is acknowledged as a benefit of Big Data, it is not the primary objective for many SMEs. This could be because SMEs are more inclined to invest in Big Data for business expansion and market growth, rather than focusing solely on cost-saving strategies.

The lower percentages for enhanced data-driven innovation (4.30%) and operational efficiency (1.08%) suggest that these aspects are not as frequently highlighted in the literature. This may be due to the challenges that SMEs face in leveraging Big Data for innovation, such as limited financial and technical resources. Similarly, the minimal focus on operational efficiency may indicate that although Big Data can improve operations, its significance is often overshadowed by its impact on business strategy and market positioning. Furthermore, the “not specified” category (1.08%) implies that a small number of studies did not clearly define performance outcomes, likely due to a more qualitative approach in their analysis.

While these results provide valuable insights into how Big Data influence various performance outcomes, it is crucial to discuss the challenges SMEs face in adopting Big Data. Many SMEs lack the technical expertise and infrastructure needed to fully utilize Big Data for innovation and operational improvements, which may explain the lower representation of innovation and efficiency outcomes. Additionally, SMEs may be overlooking potential cost-saving opportunities as they prioritize growth and revenue generation. Future research should delve deeper into these challenges and identify strategies to help SMEs overcome these barriers. This would enhance our understanding of how SMEs can better balance growth, innovation, and efficiency within their Big Data strategies.

3.5. Results of Syntheses

Figure 13 below illustrates the systematic process followed in synthesizing the results of the selected studies. It begins with the initial step of reporting synthesis results and proceeds through detailed assessments of study characteristics and biases, statistical synthesis, investigation of result variability, and sensitivity analyses. This visual representation ensures clarity in understanding the sequential steps taken to achieve a comprehensive and robust synthesis of the literature.

3.5.1. Study Characteristics and Bias Assessment

The breakdown of data collection methods in Figure 14 reveals a strong qualitative focus, with document analysis accounting for 36.56%, followed by interviews at 33.33%, observations at 25.81%, and surveys at 4.30%. This diversity offers a broad perspective, but also introduces challenges and potential biases specific to each approach. The dominance of document analysis and interviews indicates a reliance on qualitative methods that provide detailed, context-rich insights, but may also be prone to subjectivity and case-specific bias. Observations contribute valuable real-world data, while the limited use of surveys suggests that quantitative analysis is underrepresented, potentially limiting the scope for more generalizable findings.

Several key themes emerge across these studies, particularly regarding the resource and capability constraints SMEs face in adopting Big Data. Resource limitations are consistently cited as a major challenge, with SMEs lacking the financial means and skilled

personnel necessary to invest in and maintain advanced data analytic tools. This resource gap directly influences Big Data performance outcomes by inhibiting the ability of SMEs to implement data-driven strategies effectively. The lack of data literacy is another significant barrier, with insufficient skills among SME employees restricting their capacity to interpret data insights. This issue is especially problematic in light of the methodological bias towards qualitative approaches, as detailed case studies and interviews may capture nuanced individual experiences, but lack the breadth necessary to generalize about the pervasiveness of these challenges across different sectors or regions. This imbalance in data collection methods contributes to a skewed understanding of how widespread these challenges truly are.

The limited use of surveys (4.30%), which could provide more generalizable and quantitative insights, further emphasizes the risk of bias in the overall dataset. The underrepresentation of quantitative approaches restricts the ability to draw broad, statistically supported conclusions about the impact of Big Data on SME performance. Additionally, the dominance of qualitative methods, such as document analysis and interviews, could lead to an overreliance on subjective interpretations of issues like resource constraints and data literacy. This could amplify findings that are specific to certain cases and may not be applicable across a wider SME population.

When these challenges are linked to Big Data performance outcomes, it becomes evident that SMEs' internal limitations—such as resource scarcity, data illiteracy, and difficulties in integrating Big Data systems—impede their ability to effectively utilize Big Data. These constraints not only hinder operational efficiency but also prevent SMEs from using data to drive innovation and remain competitive. For instance, resource limitations restrict SMEs from acquiring essential tools for Big Data implementation, creating a cycle of underperformance and missed growth opportunities. Similarly, a lack of data literacy results in poor data interpretation, which impairs strategic decision-making and weakens SMEs' competitive edge in an increasingly data-driven market.

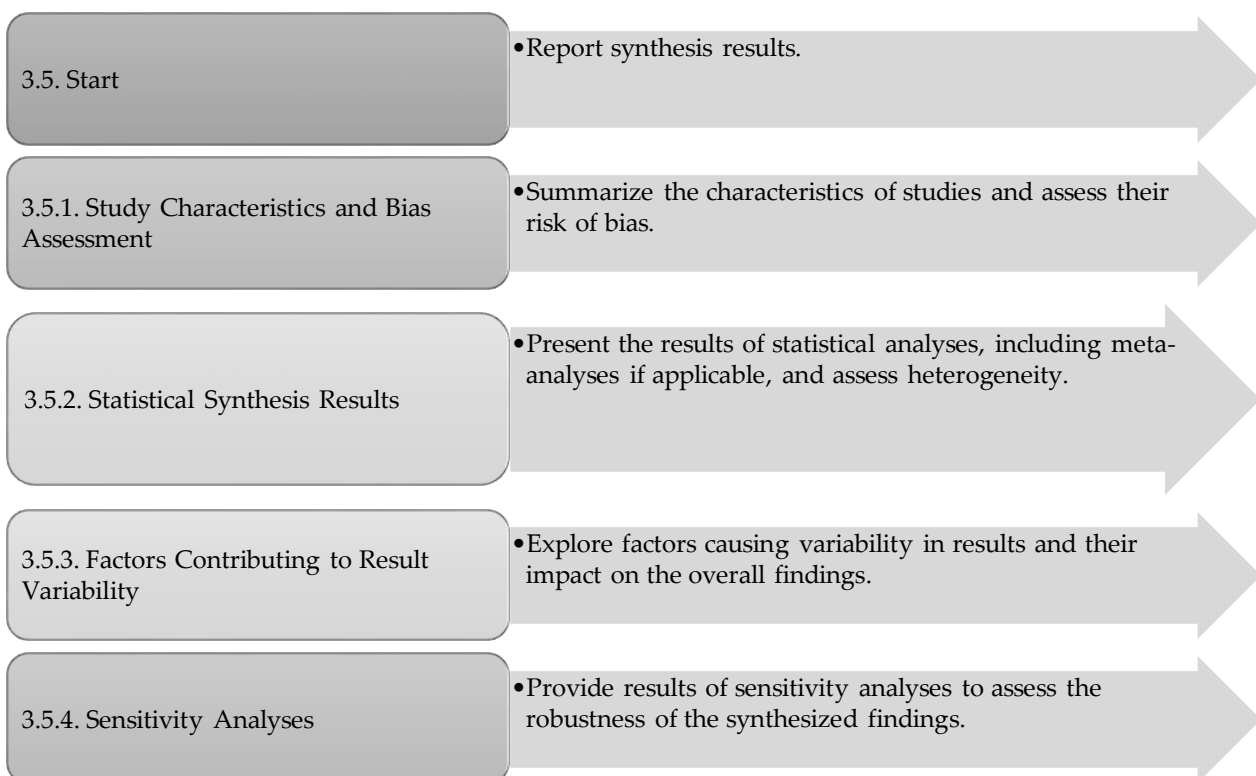


Figure 13. Synthesis systematic process.

Several gaps in the literature emerge from these methodological biases. While qualitative methods provide valuable depth and context, the lack of quantitative data collection limits our understanding of how Big Data influence SME performance across different sectors and regions. Geographical disparities in data access and technology adoption are underexplored, and there is limited focus on how sector-specific challenges shape Big Data adoption by SMEs. To address these gaps, future research should employ a mixed-method approach, incorporating more quantitative methods like surveys and longitudinal studies alongside qualitative analyses. This would enable a more comprehensive understanding of the complexities involved in Big Data implementation and their impact on SME performance.

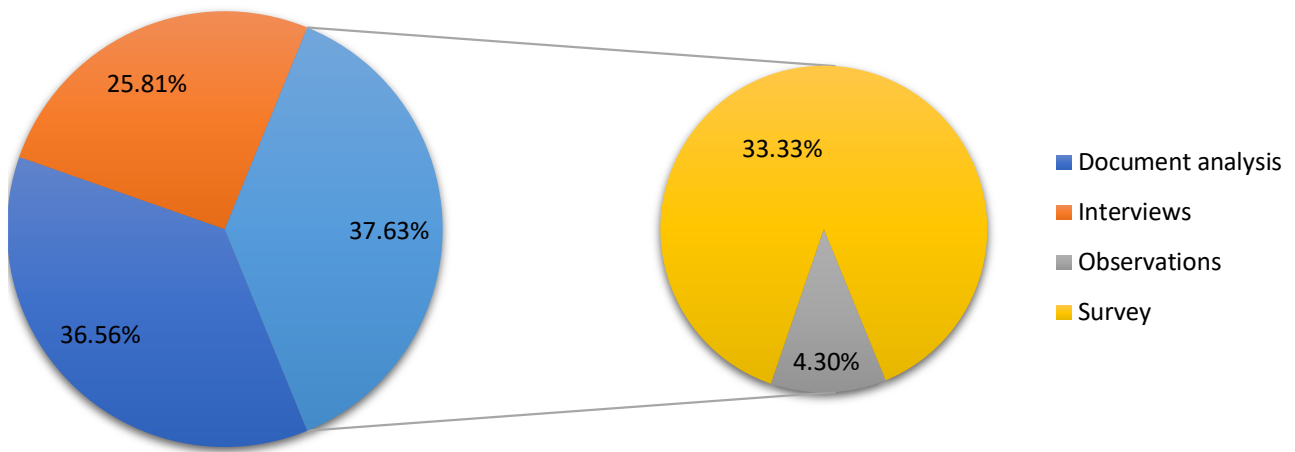


Figure 14. Study characteristics.

3.5.2. Statistical Synthesis Results

Figure 15 below provides a detailed breakdown of the analysis methods employed in the study. The pie chart reveals that “statistical analysis” represents 63% of the methods used, underscoring the study’s strong quantitative focus. In contrast, “thematic analysis” constitutes 37%, reflecting the inclusion of substantial qualitative analysis. This distribution highlights the study’s balanced approach, integrating both quantitative and qualitative methodologies to offer a comprehensive view of the research findings.

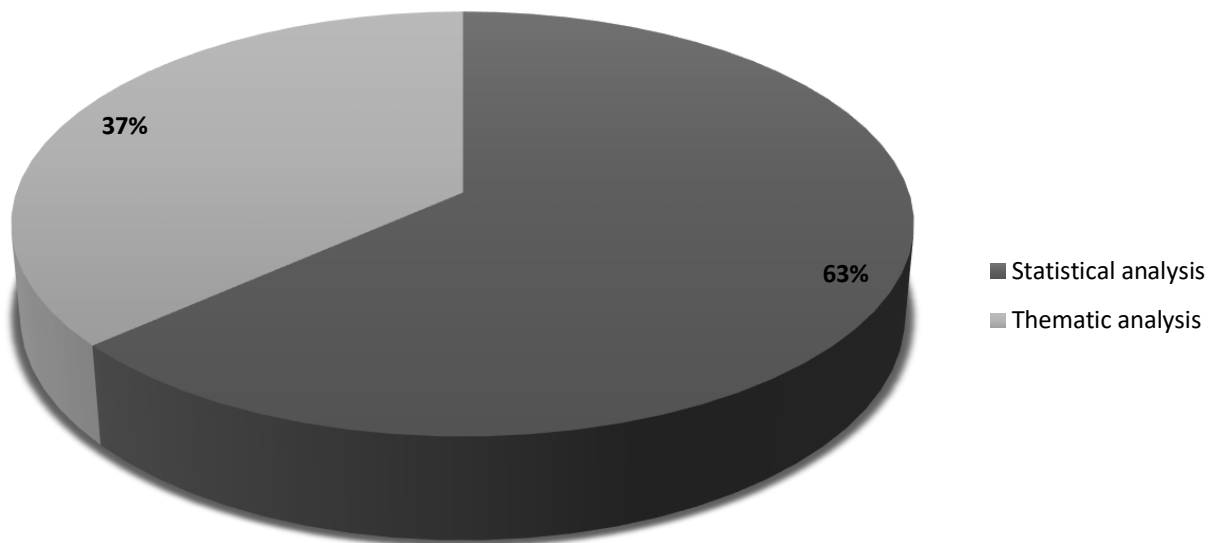


Figure 15. Analysis breakdown methods.

The figure highlights the predominance of statistical methods, which is crucial for evaluating the quantitative aspects of the study's findings. By illustrating the emphasis on statistical analysis, the chart helps in assessing the robustness of the statistical syntheses, such as meta-analysis, and their impact on the overall results. Additionally, the presence of thematic analysis underscores the inclusion of qualitative insights, providing a fuller picture of how different types of data were integrated to form the study's conclusions. This comprehensive view supports a more refined interpretation of the statistical synthesis results, ensuring that both quantitative and qualitative data are considered in the overall analysis.

3.5.3. Factors Contributing to Result Variability

Figure 16 in this section highlights key factors contributing to variability in the results observed across different professional groups, namely, data analysts, IT professionals, and small and medium-sized enterprises (SMEs). As illustrated, SMEs dominate in terms of contribution to result variability, representing 73.12% of the total, while data analysts and IT professionals show considerably lower percentages, at 13.98% and 12.90%, respectively. This significant disparity suggests that SMEs, with their diverse applications and needs, have a more substantial influence on the variability of results compared to the specialized roles of data analysts and IT professionals. The analysis of these figures provides critical insight into the different capacities and roles these groups play in shaping outcomes, underscoring the importance of focusing on SMEs when addressing performance inconsistency in Big Data and IT-related initiatives.

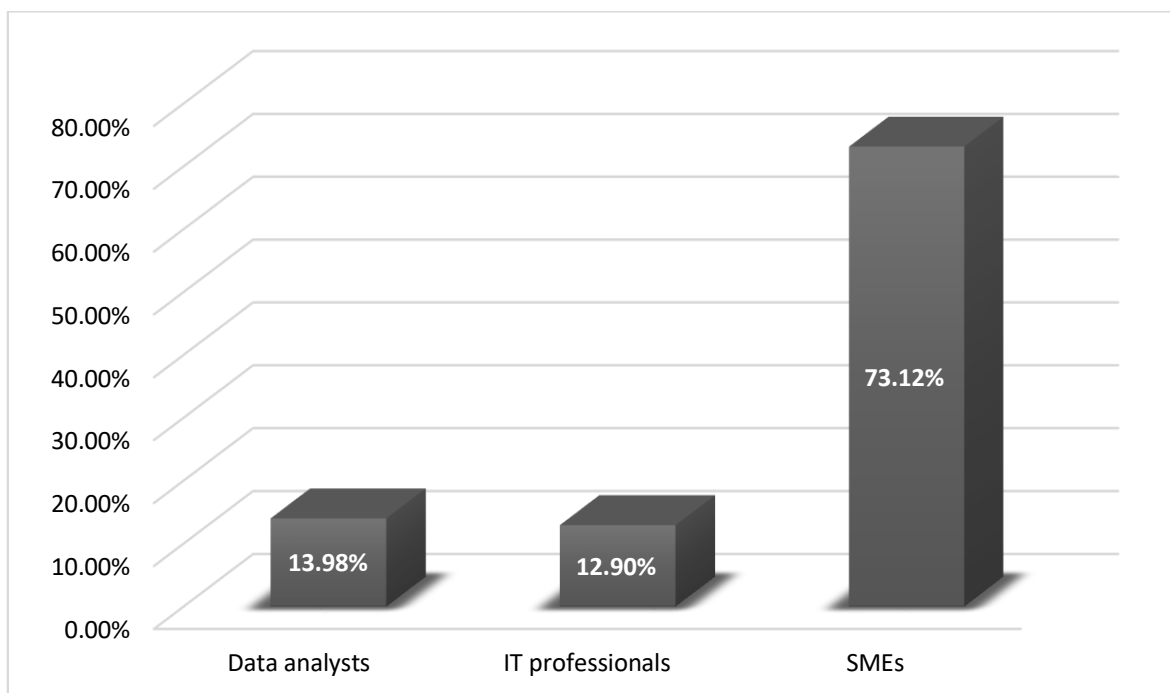


Figure 16. Sample characteristics.

3.5.4. Sensitivity Analyses

Sensitivity analyses are crucial for evaluating the robustness and reliability of data-driven models in various fields. These analyses help determine how changes in input variables impact the outcomes of a model, ensuring that the insights derived are consistent and meaningful under different conditions. Figure 17 below highlights the prominence of different analytical techniques, with data mining and predictive analytics being commonly used approaches. Notably, 44.09% of the cases did not specify the analytical technique, which may indicate a lack of transparency or clarity in methodology. However, data

mining (26.88%) and predictive analytics (16.13%) demonstrate their importance in refining models, while machine learning, at 12.90%, plays a critical role in automating complex pattern recognition. Sensitivity analyses using these techniques allow for deeper insights, especially when exact methodologies are not always clear, helping to validate the robustness of findings across multiple domains.

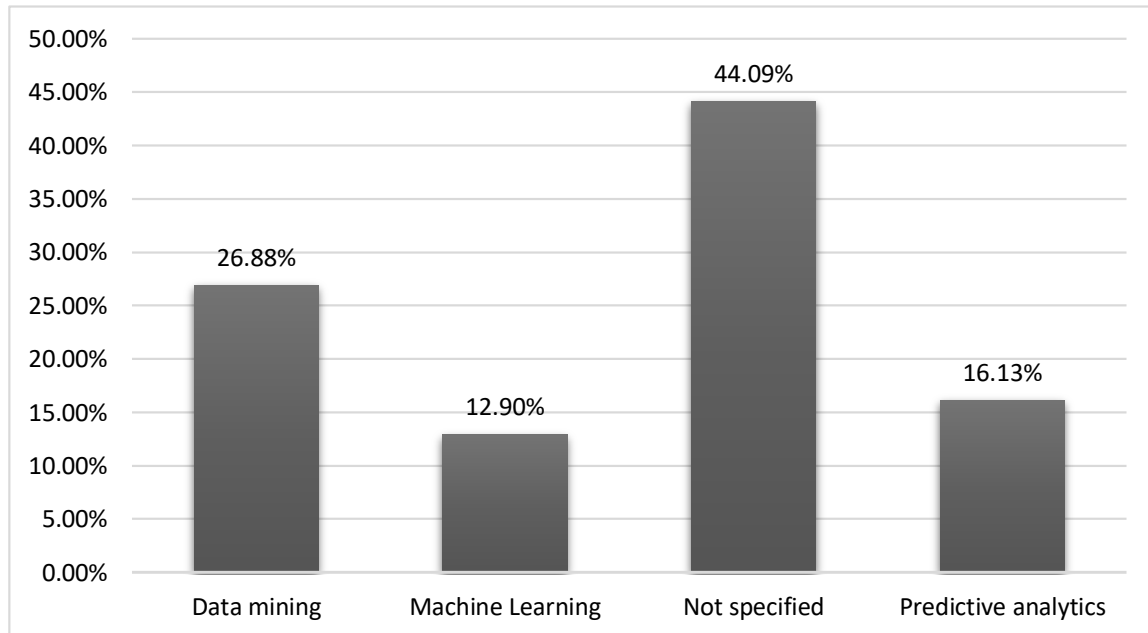


Figure 17. Utilization of data analysis techniques.

3.6. Reporting Biases

Reporting biases occur when certain research findings are more likely to be shared, leading to incomplete or skewed data interpretations. Figure 18 highlights reporting biases in the literature, with quantitative studies representing the majority at 54%, while mixed-method and qualitative studies are less common, making up 22% and 17%, respectively. This suggests a preference for quantitative research, potentially limiting the depth of insights, as mixed-method and qualitative approaches offer valuable context and a deeper understanding that quantitative studies might overlook.

The reliance on quantitative studies indicates a focus on easily measurable Big Data outcomes, such as financial performance, while qualitative insights into challenges like technical expertise or innovation receive less attention. This imbalance may obscure a complete understanding of the factors influencing Big Data adoption in SMEs. Grouping studies into broader themes, such as drivers of Big Data adoption, barriers, and industry-specific insights, can help uncover patterns and gaps in current research. This approach enriches the synthesis of results and contributes to a more balanced perspective on how Big Data impact SMEs across various contexts, providing a more comprehensive understanding of reporting biases in this field.

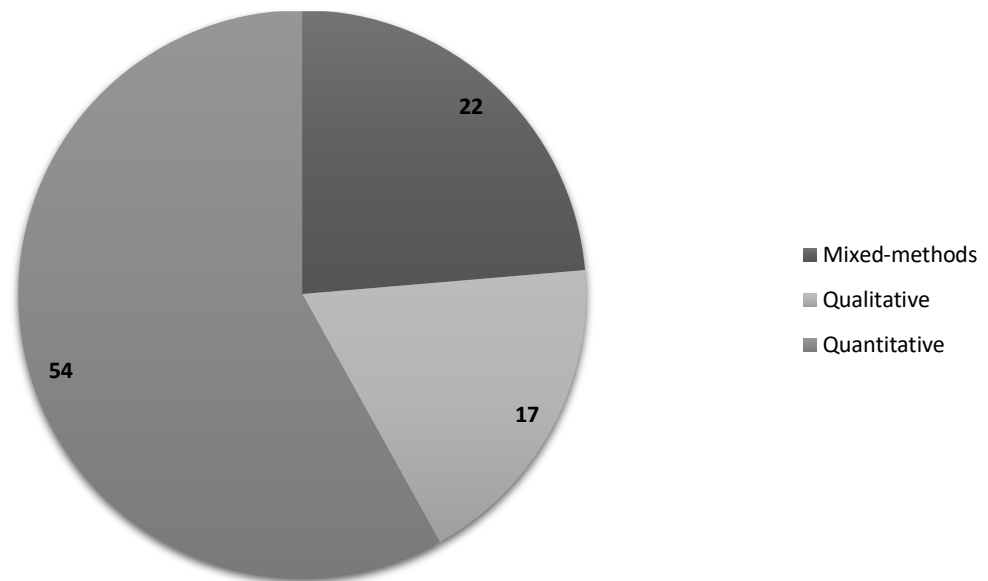


Figure 18. Distribution of study types.

3.7. Certainty of Evidence

Figure 19 shows how different data collection methods are distributed in the studies we reviewed to evaluate the impact of Big Data on SMEs’ performance. This visual representation helps us understand how the choice of methods affects the reliability of the study’s conclusions.

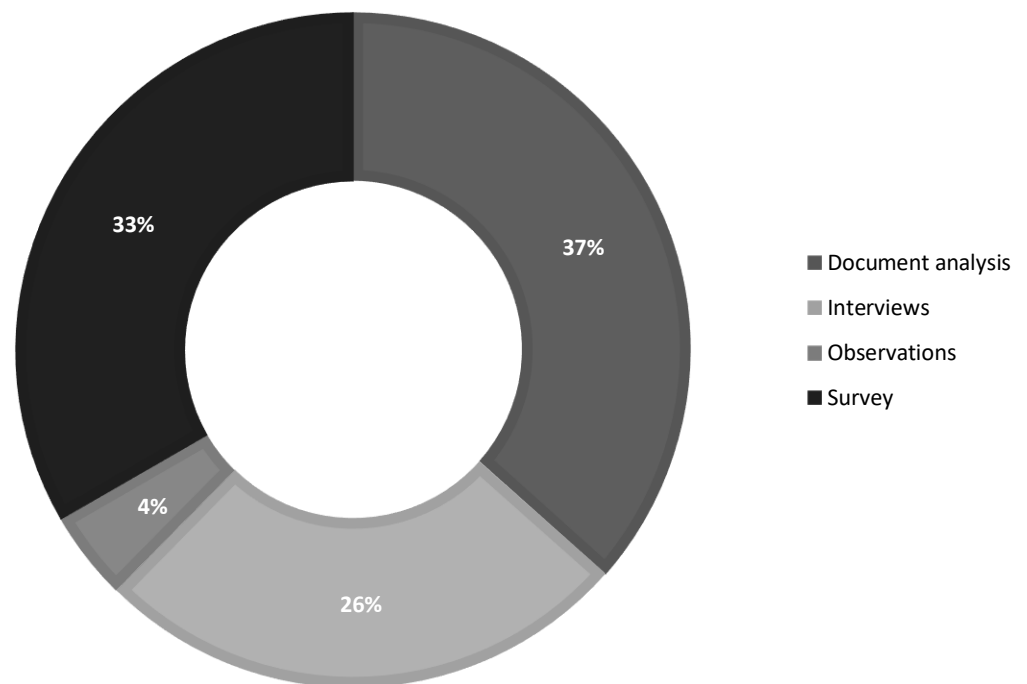


Figure 19. Distribution of data collection methods.

Document analysis, which constitutes 37% of the methods used, provides a solid foundation for the evidence. This method relies on existing records and documents, which are typically stable and verifiable. As a result, document analysis contributes significantly to the certainty of the findings by offering consistent and well-documented data that enhance the reliability of the evidence. Interviews make up 26% of the methods and offer rich, detailed insights that can deepen the understanding of the subject matter. However,

the certainty of the findings from interviews can be influenced by respondent biases and subjective interpretations. For instance, if interviewees have differing perspectives or personal agendas, their responses may introduce variability into the results, which can affect the overall certainty.

Surveys account for 33% of the methods and are valuable for gathering data from a wide range of SMEs. Nevertheless, the certainty of survey-based findings can be impacted by response biases and limitations in sample representativeness. Response biases occur when survey participants provide socially desirable answers rather than their true opinions, which can skew the results. Additionally, if the survey sample is not representative of the broader SME population, the findings may not be generalizable, thus affecting the certainty of the conclusions. Observations, which make up only 4% of the methods, contribute minimally to the certainty of the evidence due to their limited scope and application. Observations are often constrained by their specific context and may not capture the broader patterns or trends relevant to the study, reducing their overall impact on the certainty of the findings.

Figure 19 illustrates how each data collection method impacts the certainty of the evidence. Document analysis provides reliable and consistent data, while interviews and surveys introduce various degrees of variability due to potential biases and representativeness issues. Observations, though insightful, have a limited effect on the overall certainty. By employing a combination of these methods, the study achieves a comprehensive understanding of how Big Data affect SME performance, though with varying levels of confidence in the conclusions drawn. This detailed explanation demonstrates how Figure 19 supports the analysis of the certainty of evidence in this study.

4. Practical Recommendations

4.1. Key Findings and Strategic Implications for Business Leaders

This section presents the critical findings from our systematic review of Big Data (BD) adoption and its impact on SMEs across various industries. The findings highlight the strategic opportunities and challenges that business leaders must consider when integrating BD into their operations. By understanding the key drivers and expected outcomes of BD technologies, business leaders can make more informed decisions that enhance performance and competitiveness. Table 13 organizes these insights by industry, providing business leaders with actionable strategies and a clear understanding of the opportunities and challenges specific to their sectors. Additionally, three critical columns—opportunities, challenges, and strategic drivers—are included to further emphasize how leaders can harness BD for growth and innovation while navigating potential obstacles.

The findings summarized in Table 11 illustrate the widespread influence of Big Data on key business functions, such as inventory management, process optimization, patient care, risk modeling, and route optimization. For SMEs, the integration of BD technologies presents both significant opportunities and challenges. Opportunities such as enhanced forecasting, real-time insights, and personalized services can significantly improve business performance. However, challenges like data literacy gaps, privacy concerns, and high infrastructure costs continue to hinder full adoption.

Strategic drivers such as BD technology integration, operational excellence, and data-driven decision-making are crucial for overcoming these obstacles and unlocking the full potential of Big Data. By aligning their strategies with these drivers, business leaders can expect improved efficiency, cost savings, and long-term innovation capabilities. Future research should focus on developing industry-specific BD adoption frameworks that address the unique needs and challenges of SMEs across various sectors.

Table 13. Key findings and strategic implications for business leaders.

Industry	Key Finding	Strategic Implications for Business Leaders	Opportunities	Challenges	Relevance to Proposed Systematic Review	Strategic Drivers	Expected Outcome
Retail	Big Data enable demand forecasting, optimizing stock levels	Leaders should prioritize data-driven decision-making for inventory management	Use Big Data for precision forecasting	Data literacy and technology integration challenges	Aligns with findings on operational efficiency	Integration of BD technologies and skills development	Improved inventory management and reduced stockouts
Manufacturing	Big Data improve process optimization and reduce downtime	Invest in real-time data analytics for machinery performance monitoring	Real-time insights into equipment health	High costs of analytics infrastructure	Related to BD's role in process innovation	Emphasis on operational excellence and cost-effectiveness	Reduced downtime, increased productivity
Healthcare	Big Data enhance patient outcome tracking and predictive healthcare	Utilize predictive analytics for personalized treatments	Improved patient care and outcomes	Privacy concerns, data security issues	Relevant to BD in decision-making improvements	Focus on data-driven healthcare solutions	Enhanced patient satisfaction and care quality
Finance	Big Data allow for advanced risk modeling and fraud detection	Develop comprehensive risk management strategies using analytics	Better fraud detection and risk mitigation	Lack of skilled data analysts	Tied to BD's impact on risk management strategies	Drive innovation in financial analysis tools	Reduced financial risk and fraud cases
Logistics	Data analytics improves route optimization and reduces fuel consumption	Adopt analytics for logistics and transportation management	Better route planning, cost reduction	Integration with existing systems	Linked to resource optimization through BD	Focus on eco-friendly, cost-efficient operations	Improved efficiency, lower operational costs

4.2. Proposed Decision-Making Framework for Implementation

This section introduces a detailed breakdown of steps for implementing Big Data (BD) across different industries. By focusing on industry-specific requirements, Table 14 outlines key steps in the adoption process, highlighting how each industry can leverage BD to drive performance, operational efficiency, and innovation. The steps include framework focus, key features, strategic drivers, expected outcomes, and connections to the proposed study. The decision-making framework outlined in Table 14 offers a structured approach to BD implementation across industries, highlighting the critical steps needed to leverage data-driven insights for operational improvements. Each step is tailored to the unique needs of specific industries, focusing on key features such as predictive analytics, automation, and risk management.

By identifying strategic drivers—such as operational efficiency, customer satisfaction, and cost reduction—this framework enables SMEs to optimize performance, innovate, and maintain competitiveness in a data-driven environment. The expected outcomes reflect practical benefits, such as reduced costs, improved customer experiences, and enhanced operational efficiency. This framework is aligned with the systematic review's findings, ensuring that the steps proposed here address the real-world challenges and opportunities that SMEs face in BD adoption. It provides a roadmap for business leaders to navigate the complexities of data integration while achieving meaningful, long-term outcomes.

4.3. Proposed Best Practices for Successful Implementation

This section outlines best practices tailored to different industries for the successful implementation of Big Data (BD) in SMEs. By considering industry-specific operational challenges, strategic drivers, and expected impacts, Table 15 provides practical guidelines for ensuring effective adoption and utilization of BD technologies. The practices tabulated are directly tied to the findings from the systematic review, ensuring that they address the real-world conditions faced by SMEs.

The best practices outlined in Table 15 are designed to help SMEs across various industries successfully adopt BD technologies by addressing their unique operational challenges. By identifying strategic drivers such as customer satisfaction, cost-effectiveness, and compliance, these practices ensure that SMEs can fully leverage BD to improve performance, reduce operational costs, and enhance competitiveness. Each best practice is closely tied to the findings from the systematic review, ensuring alignment with the real-world challenges and opportunities that SMEs encounter when adopting BD. This comprehensive approach provides business leaders with actionable strategies to ensure the successful implementation of BD, helping SMEs optimize both short-term operational efficiency and long-term strategic growth.

Table 14. Proposed decision-making framework for implementation.

Industry	Step	Framework Focus	Key Features	Strategic Drivers	Expected Outcome	Ties to Proposed Study
Retail	1. Assess Data Needs	Identifying critical data sources for forecasting	Customer behavior, sales data, market trends	Data-driven decision-making, customer-centric strategies	Optimized stock levels, reduced overstock/stockouts	Aligned with operational efficiency and demand forecasting
	2. Implement Real-Time Analytics	Real-time analysis of customer preferences	Real-time sales tracking, dynamic pricing	Enhanced customer engagement, personalized marketing	Increased customer satisfaction, improved sales	Links to BD's impact on customer satisfaction
	3. Optimize Inventory Management	Data-driven inventory control	Inventory turnover analysis, stock level monitoring	Efficient resource allocation, minimized waste	Reduced inventory costs, faster restocking	Ties to BD's role in operational efficiency
	4. Monitor Market Trends	Predicting future market changes	Predictive analytics, market sentiment tracking	Business agility, competitive positioning	Improved market responsiveness	Relevant to BD's role in competitive advantage
Manufacturing	1. Conduct Data Audits	Assess existing production and process data	Production KPIs, machinery data	Operational excellence, process optimization	Reduced downtime, improved production rates	BD in process innovation
	2. Integrate Predictive Maintenance	Predict machine failures using data	Machine learning, sensor data	Cost-effectiveness, reduced equipment failure risk	Improved asset lifespan, reduced maintenance costs	Relevant to operational efficiency
	3. Implement Quality Control Tools	Data-driven monitoring of product quality	Real-time quality checks, anomaly detection	Enhanced product consistency, reduced waste	Higher product quality, minimized defects	Links to BD in quality control
	4. Automate Workflow Processes	Using data to automate production workflows	Robotics, real-time process monitoring	Productivity, cost-effectiveness	Optimized production, reduced manual labor	Relevant to BD in productivity
Healthcare	1. Ensure Data Privacy Compliance	Protecting patient data during BD use	Data encryption, compliance checks	Data security, patient trust	Increased patient data security, compliance	Relevant to ethical data management
	2. Implement Predictive Analytics	Using data for predicting patient outcomes	Predictive models, health data analysis	Improved patient outcomes, proactive care	Enhanced healthcare delivery, lower readmission rates	Relevant to BD in healthcare performance
	3. Streamline Clinical Processes	Optimizing operational processes in healthcare	Process mapping, resource allocation tools	Cost-effectiveness, process optimization	Reduced waiting times, improved service quality	Tied to operational improvements in healthcare
	4. Utilize AI for Diagnosis Support	Supporting diagnosis with AI-based data tools	Machine learning, AI-assisted diagnostics	Accuracy in diagnosis, faster treatment decisions	Improved diagnostic accuracy, reduced medical errors	Relevant to innovation in healthcare delivery
Finance	1. Build Risk Management Models	Use BD to enhance risk management strategies	Fraud detection, credit risk analysis	Improved financial analysis, fraud mitigation	Reduced financial risk, better credit assessments	Tied to risk management in financial performance
	2. Optimize Investment Decisions	Data-driven investment forecasting	Predictive models, market analysis	Investment efficiency, risk-adjusted returns	Higher returns, optimized portfolio management	Relevant to BD in financial decision-making
	3. Automate Compliance Monitoring	Ensure regulatory compliance through data	Real-time monitoring, regulatory data checks	Compliance risk reduction, regulatory adherence	Reduced compliance risks, streamlined audits	Relevant to BD in regulatory management
	4. Improve Customer Personalization	Enhancing customer services using data	Customer behavior analysis, financial trends	Customer satisfaction, loyalty	Increased customer retention, personalized services	Tied to customer experience enhancement

Table 14. Cont.

Industry	Step	Framework Focus	Key Features	Strategic Drivers	Expected Outcome	Ties to Proposed Study
Logistics	1. Assess Supply Chain Data	Data-driven insights on supply chain operations	Route data, delivery time analysis	Cost-effectiveness, sustainable operations	Reduced fuel costs, optimized delivery routes	Aligned with BD in supply chain optimization
	2. Optimize Fleet Management	Monitoring and improving fleet performance	GPS data, fuel consumption tracking	Operational efficiency, reduced carbon footprint	Increased fleet efficiency, reduced operational costs	Relevant to eco-friendly logistics strategies
	3. Implement Predictive Route Planning	Dynamic route optimization using BD	Real-time traffic data, predictive route models	Faster deliveries, cost reduction	Improved delivery times, optimized supply chain	Links to data-driven logistics
	4. Manage Inventory Efficiently	Enhance supply chain inventory control	Real-time inventory tracking, stock monitoring	Reduced stockouts, cost-effectiveness	Optimized supply chain, minimized inventory costs	Tied to BD in supply chain management

4.4. Proposed Metrics and KPIs for Measuring Performance

This section outlines the key metrics and KPIs (key performance indicators) essential for measuring performance across various industries that utilize Big Data (BD) technologies. The metrics were selected based on their relevance to enhancing operational efficiency, customer satisfaction, innovation, and financial performance. The industries examined include retail, manufacturing, healthcare, finance, and logistics, each of which faces unique challenges that can be addressed by strategically implementing Big Data solutions. The proposed metrics and KPIs in Table 16 focus on the core areas critical to improving SME performance, tying them to the findings from our systematic review. The priorities assigned to each metric reflect their importance in driving performance outcomes within their respective industries.

The analysis of the proposed metrics and KPIs across these industries highlights the central role that Big Data plays in enhancing business performance. Key findings show that industries prioritize different metrics based on their operational needs, but common drivers include improving customer satisfaction, optimizing operational efficiency, and boosting financial outcomes. In retail, customer retention and average order value are the highest priorities, reflecting the industry's focus on customer engagement and profitability. Manufacturing prioritizes production throughput and order fulfillment cycle time, emphasizing operational efficiency and supply chain optimization. Healthcare places high importance on patient satisfaction and treatment success rates, demonstrating the critical role of Big Data in improving clinical outcomes. The finance industry heavily focuses on loan default rates and net interest margin, both vital for profitability and risk management. Logistics emphasizes on-time delivery and shipment tracking accuracy as essential metrics for maintaining high customer satisfaction and operational efficiency.

The priority rankings within each industry underscore the strategic emphasis of Big Data in addressing industry-specific challenges. Future research should focus on how these KPIs can be further refined, particularly by leveraging emerging Big Data technologies to enhance measurement accuracy and support long-term growth across various sectors.

4.5. Proposed Industry-Specific Frameworks

In this section, we present the proposed industry-specific frameworks for the implementation of Big Data solutions across various sectors. Each industry requires tailored approaches to leverage the full potential of Big Data, addressing BD's unique operational challenges while driving strategic outcomes. Table 17 provides a detailed breakdown of key framework components, implementation steps, and expected outcomes for the retail, manufacturing, healthcare, finance, and logistics industries.

Table 15. Proposed best practices for successful implementation.

Industry	Best Practice	SME Type	Operational Challenges	Strategic Drivers	Expected Impact	Ties to Systematic Review Findings
Retail	Adopt real-time analytics for customer data	E-Commerce, Brick-and-Mortar	Managing large volumes of customer data	Customer-centric strategies, real-time decision-making	Improved customer engagement, increased sales	Aligned with operational efficiency and customer satisfaction
	Integrate demand forecasting tools	Apparel, Grocery Retailers	Stockouts and inventory mismanagement	Inventory control, predictive demand analysis	Reduced inventory costs, improved stock levels	Relevant to BD's role in operational efficiency
	Utilize dynamic pricing models	Online Retailers	Staying competitive in fluctuating markets	Market responsiveness, competitive positioning	Increased market competitiveness, optimized pricing strategies	Ties to competitive advantage in the systematic review
Manufacturing	Implement predictive maintenance systems	Light Manufacturing, Electronics	Equipment breakdown and downtime	Cost-effectiveness, resource management	Reduced downtime, extended equipment lifespan	Relevant to BD's role in operational efficiency
	Utilize automated quality control	Pharmaceuticals, Food Processing	Quality consistency and compliance	Regulatory adherence, product consistency	Improved product quality, minimized waste	Aligned with BD's role in process optimization
	Leverage workflow automation	Automotive, Heavy Machinery	Complex workflows, production bottlenecks	Operational excellence, productivity	Enhanced production rates, optimized resource allocation	Ties to productivity enhancements in SMEs
Healthcare	Prioritize data security and privacy compliance	Clinics, Healthcare Facilities	Data breaches and patient trust	Data security, regulatory compliance	Increased patient trust, adherence to data privacy regulations	Relevant to BD's role in ethical data management
	Use AI for diagnostic support	Hospitals, Diagnostic Centers	Diagnostic errors and delays	Diagnostic accuracy, faster treatment decisions	Improved diagnostic accuracy, reduced errors	Aligned with innovation in healthcare delivery
	Optimize patient flow through predictive analytics	Primary Care, Urgent Care	Patient congestion, long waiting times	Process optimization, patient satisfaction	Reduced waiting times, improved service delivery	Tied to operational improvements in healthcare

Table 15. Cont.

Industry	Best Practice	SME Type	Operational Challenges	Strategic Drivers	Expected Impact	Ties to Systematic Review Findings
Finance	Enhance risk management with real-time analytics	Fintech, Banks	Fraud detection, risk assessment challenges	Fraud mitigation, risk-adjusted decision-making	Reduced financial risk, improved credit assessments	Aligned with risk management in financial performance
	Automate compliance reporting	Financial Services, Insurance	Complex regulatory compliance requirements	Compliance risk reduction, streamlined audits	Reduced compliance risk, improved audit readiness	Relevant to regulatory management through BD
	Leverage predictive analytics for investment strategies	Investment Firms, Asset Management	Market volatility and forecasting inaccuracy	Market foresight, investment efficiency	Increased returns, optimized portfolio management	Aligned with financial decision-making strategies
Logistics	Optimize supply chain management with data insights	Freight, Delivery Services	Inefficient inventory control, high fuel costs	Supply chain visibility, cost-effectiveness	Reduced operational costs, optimized deliveries	Relevant to supply chain management and efficiency
	Implement predictive route optimization	Fleet Management, Last-Mile Delivery	Route inefficiencies, delivery delays	Route optimization, customer satisfaction	Faster delivery times, reduced fuel consumption	Tied to data-driven logistics strategies
	Leverage real-time tracking for inventory	Warehousing, Distribution	Inventory mismanagement, stockouts	Inventory optimization, cost reduction	Optimized inventory levels, reduced stockouts	Aligned with operational efficiency in logistics

Table 16. Proposed metrics and KPIs for measuring performance.

Industry	Key Metrics/KPIs	Measurement Focus	Strategic Drivers	Expected Outcome	Ties to Systematic Review Findings	Priority (1 = Highest, 2 = Medium, 3 = Low)
Retail	Customer Retention Rate	Customer Engagement	Customer Loyalty, Brand Experience	Higher retention, increased repeat business	Big Data improving customer targeting and loyalty	1
	Average Order Value	Sales Performance	Profitability, Customer Spending	Higher sales, increased revenue	Data analytics boosting profitability	1
	Inventory Turnover	Inventory Management	Stock Optimization, Demand Forecasting	Reduced overstock/stockouts, cost control	BD improving demand forecasting and stock management	2
	Conversion Rate	Marketing Efficiency	Sales Funnel Optimization, Digital Engagement	Increased conversion, better ROI on marketing	Insights from Big Data on consumer behavior and conversion	2
Manufacturing	Production Throughput	Operational Efficiency	Cost Reduction, Process Optimization	Enhanced productivity, lower operational costs	Big Data driving operational efficiency and innovation	1
	Defect Rate	Quality Control	Product Quality, Waste Reduction	Improved product quality, less waste	Impact of BD on maintaining high-quality standards	2
	Equipment Downtime	Maintenance Efficiency	Predictive Maintenance, Cost Control	Increased uptime, reduced maintenance costs	Big Data predictive analytics for maintenance efficiency	2
	Order Fulfillment Cycle Time	Supply Chain Management	Lead-Time Reduction, Demand Fulfillment	Faster fulfillment, Improved customer satisfaction	Enhanced supply chain operations through data insights	1
Healthcare	Patient Satisfaction Score	Service Quality	Patient Care, Service Delivery	Improved care outcomes, patient trust	Data analytics improving patient satisfaction	2
	Average Treatment Cost	Cost-Effectiveness	Healthcare Cost Management	Lower costs, better allocation of resources	BD supporting resource optimization in healthcare	2
	Treatment Success Rate	Clinical Outcomes	Quality of Care, Patient Outcomes	Improved health outcomes, fewer readmissions	Big Data predictive analysis for patient care	1

Table 16. Cont.

Industry	Key Metrics/KPIs	Measurement Focus	Strategic Drivers	Expected Outcome	Ties to Systematic Review Findings	Priority (1 = Highest, 2 = Medium, 3 = Low)
Finance	Loan Default Rate	Credit Risk Management	Risk Reduction, Customer Creditworthiness	Lower default rates, increased risk mitigation	BD enhancing credit scoring and risk analysis	1
	Net Interest Margin	Profitability	Revenue Generation, Cost of Funding	Higher profits, improved loan and deposit management	Big Data improving financial decision-making	1
	Fraud Detection Rate	Security and Compliance	Transaction Monitoring, Fraud Prevention	Reduced fraud losses, increased compliance	Data-driven fraud prevention and detection strategies	2
	Customer Acquisition Cost	Customer Acquisition	Marketing Efficiency, Profitability	Lower acquisition costs, better customer targeting	Insights from BD for reducing acquisition costs	2
Logistics	On-Time Delivery Rate	Supply Chain Management	Delivery Optimization, Customer Satisfaction	Improved delivery times, increased customer trust	Big Data optimizing logistics and supply chain processes	1
	Transportation Cost per Mile	Operational Efficiency	Cost Control, Route Optimization	Lower costs, increased operational efficiency	Big Data improving transport logistics and cost-effectiveness	2
	Fleet Downtime	Asset Management	Maintenance Planning, Cost Control	Reduced downtime, lower maintenance costs	BD enabling predictive maintenance for fleet management	2
	Shipment Tracking Accuracy	Customer Experience	Transparency, Service Quality	Better shipment tracking, Improved customer satisfaction	Real-time data insights enhancing shipment tracking	1

Table 17. Proposed industry-specific frameworks.

Industry	Framework Component	Key Focus Area	Implementation Steps	Challenges Addressed	Strategic Drivers	Expected Outcome	Ties to Systematic Review Findings
Retail	Data-Driven Marketing	Customer Engagement	Step 1: Define target segments based on data analytics Step 2: Optimize marketing channels with insights Step 3: Leverage predictive analytics for personalized offers	Addressing customer retention, personalization gaps	Customer Loyalty, Sales Growth	Improved customer targeting, higher sales	Data supporting decision-making and customer loyalty
	Inventory Optimization	Supply Chain Management	Step 1: Implement demand forecasting tools Step 2: Utilize BD for inventory tracking Step 3: Automate restocking with predictive models	Stockouts, overstocking, supply chain disruptions	Operational efficiency, Cost Reduction	Reduced stockouts, improved supply chain management	BD enhancing stock management and forecasting
Manufacturing	Predictive Maintenance	Equipment Efficiency	Step 1: Use sensors for real-time equipment monitoring Step 2: Analyze data to predict maintenance needs Step 3: Automate alerts for proactive maintenance actions	Equipment downtime, high maintenance costs	Operational Efficiency, Cost Control	Increased equipment uptime, reduced costs	Big Data improving predictive maintenance
	Process Optimization	Production Output	Step 1: Collect data from production processes Step 2: Analyze workflow bottlenecks Step 3: Implement data-driven process adjustments	Inefficiencies in production, high defect rates	Process Optimization, Quality Control	Enhanced productivity, lower defect rates	BD streamlining production efficiency

Table 17. Cont.

Industry	Framework Component	Key Focus Area	Implementation Steps	Challenges Addressed	Strategic Drivers	Expected Outcome	Ties to Systematic Review Findings
Healthcare	Patient Care Analytics	Clinical Outcomes	Step 1: Aggregate patient data from multiple sources Step 2: Use predictive models to identify at-risk patients Step 3: Integrate data into care plans for personalized treatment	High treatment costs, patient readmissions	Patient Satisfaction, Quality of Care	Improved patient outcomes, lower readmission rates	Big Data driving patient care and clinical success
	Resource Allocation	Healthcare Efficiency	Step 1: Track usage of medical resources in real time Step 2: Use BD to forecast resource needs Step 3: Automate resource scheduling based on demand	Inefficient resource usage, overcrowded facilities	Cost Control, Efficiency	Optimized resource usage, cost savings	Data supporting optimal resource allocation
Finance	Credit Risk Assessment	Risk Management	Step 1: Collect customer financial data Step 2: Analyze credit risk using BD models Step 3: Implement automated risk scoring systems	Loan default, poor risk analysis	Risk Mitigation, Profitability	Lower default rates, better risk management	Big Data improving credit scoring and risk assessment
	Fraud Detection	Security and Compliance	Step 1: Implement real-time transaction monitoring systems Step 2: Use machine learning for anomaly detection Step 3: Automate fraud alerts and responses	Fraudulent transactions, security risks	Compliance, Risk Control	Reduced fraud incidents, improved security	Data-driven fraud prevention

Table 17. Cont.

Industry	Framework Component	Key Focus Area	Implementation Steps	Challenges Addressed	Strategic Drivers	Expected Outcome	Ties to Systematic Review Findings
Logistics	Route Optimization	Supply Chain Efficiency	Step 1: Use GPS data for real-time route tracking Step 2: Implement predictive analytics for delivery time estimation Step 3: Automate route adjustments based on traffic patterns	Delays in delivery, high transportation costs	Customer Satisfaction, Cost Control	Faster deliveries, lower transportation costs	BD optimizing logistics and delivery routes
	Fleet Management	Operational Efficiency	Step 1: Collect data from fleet sensors Step 2: Analyze vehicle performance data Step 3: Use BD insights for fleet maintenance scheduling	Fleet downtime, inefficient asset management	Operational Efficiency, Asset Utilization	Reduced downtime, improved fleet performance	Big Data improving asset and fleet management

4.6. Real-World Case Studies Related to Proposed Systematic Review

In this section, we explore real-world case studies across various industries to demonstrate the successful implementation of Big Data technologies. The cases highlighted offer insights into how companies have leveraged Big Data to improve operational efficiency, customer satisfaction, and profitability. By analyzing these real-world examples, we aim to draw parallels with the challenges and opportunities presented in small and medium-sized enterprises (SMEs), as tabulated in Table 18.

The case studies reveal that industries such as retail, healthcare, finance, logistics, and entertainment have successfully adopted Big Data technologies to improve their operations and business outcomes. For instance, Amazon's recommendation engine has significantly boosted its sales, while Visa has reduced fraud through real-time data analysis. These outcomes align with the findings from our systematic review, which underscore the potential of Big Data to drive performance improvements, though SMEs often face unique challenges such as resource limitations and data literacy issues. Each case provides valuable lessons on overcoming barriers to Big Data adoption, including leveraging advanced analytics to predict customer behavior and optimizing resource management to enhance decision-making processes. These examples offer a benchmark for how SMEs can strategically implement Big Data to achieve similar results, though industry-specific adaptations will be necessary.

4.7. Proposed Roadmap for SMEs and Policy Recommendations

This section outlines a strategic roadmap for implementing Big Data and digital solutions within small and medium-sized enterprises (SMEs) across key industries, as shown in Table 19. Focusing on specific policy frameworks, strategic drivers, and expected outcomes, this roadmap provides a detailed guide to help SMEs navigate the complexities of digital transformation while aligning with industry standards and global best practices. The roadmap is categorized into four steps for each industry, emphasizing the integration of digital tools, workforce training, and strategic decision-making. For each industry, the key challenges and opportunities tied to the adoption of digital tools, such as AI, IoT, and blockchain, are considered, allowing for a practical, actionable framework tailored to SMEs' needs.

The roadmap outlined for each industry highlights the critical steps SMEs can take to enhance their digital transformation, operational efficiency, and competitiveness. By aligning these steps with relevant policy frameworks, such as the EU Digital Strategy for SMEs and Industry 4.0, business leaders can make informed decisions that drive innovation, reduce costs, and improve customer satisfaction. Strategic drivers, such as data-driven innovation, blockchain adoption, and upskilling the workforce, are key enablers in achieving the expected outcomes of improved productivity, reduced costs, and enhanced competitiveness. Each industry faces unique challenges, but the roadmap offers a structured, step-by-step approach to overcome these challenges and capitalize on opportunities through digital transformation.

Table 18. Real-world case studies related to proposed systematic review.

Industry	Case Study	Implementation	Outcome	Reference
Retail	Amazon	Amazon utilizes Big Data for personalized recommendations, price optimization, and shipping logistics. It leverages customer data from browsing habits and voice interactions with Alexa.	Increased sales by 35% from recommendations, improved customer retention, and enhanced operational efficiency.	https://www.businesstechweekly.com/ (Accessed on 20 September 2024)
Retail	Walmart	Walmart harnesses Big Data through Hadoop and NoSQL to analyze customer preferences in real time, optimizing product recommendations and supply chain operations.	Boosted conversion rates, enhanced customer satisfaction, and streamlined supply chain processes.	https://datafortune.com/ (Accessed on 20 September 2024)
Finance	Visa	Visa employs Big Data to detect fraudulent transactions in real time by analyzing billions of transaction records across the globe.	Minimized fraudulent transactions, leading to greater trust in the Visa network and enhanced customer protection.	https://usa.visa.com/ (Accessed on 20 September 2024)
Logistics	UPS	UPS uses Big Data to optimize delivery routes and improve fleet management, utilizing its ORION system to analyze vehicle sensor data and GPS information.	Saved millions of gallons of fuel annually, reduced carbon emissions, and improved delivery times.	https://hbr.org/ (Accessed on 20 September 2024)
Entertainment	Netflix	Netflix employs Big Data for content recommendations, tracking user preferences, viewing patterns, and ratings to curate personalized viewing experiences.	Increased subscriber retention, personalized user experiences, and higher content engagement rates.	https://towardsdatascience.com (Accessed on 20 September 2024)

Table 19. Proposed roadmap for SMEs and policy recommendations.

Industry	Roadmap Focus	Policy Framework	Strategic Link	Strategic Drivers	Expected Outcome	Ties to Proposed Study
Retail	Step 1: Adopt digital platforms such as e-commerce and CRM	EU Digital Strategy for SMEs	Improve digital competitiveness	Digital transformation and customer engagement	Increased market reach and improved customer satisfaction	Supports findings on digital tools improving SME performance
	Step 2: Implement data analytics for customer behavior insights		Enhance customer targeting through data	Data-driven innovation	Customized marketing campaigns, higher customer retention	Links to improved decision-making and customer insights
	Step 3: Transition to digital payments	EU Fintech Policy	Align with global e-payment trends	Digital payment systems	Improved transaction efficiency and trust	Reinforces tech adoption for operational efficiency
	Step 4: Train workforce in data utilization	EU Skills Agenda	Boost workforce competency in data analytics	Upskilling and employee training	Enhanced data literacy and workforce productivity	Aligns with digital skills improvement in SMEs
Manufacturing	Step 1: Implement IoT for process automation	Industry 4.0	Integrate advanced manufacturing technologies	IoT, automation, and smart manufacturing	Increased operational efficiency, reduced downtime	Aligns with findings on operational efficiency through tech adoption
	Step 2: Utilize predictive maintenance tools		Reduce equipment failure rates	Data analytics and predictive algorithms	Improved machine longevity and reduced maintenance costs	Reinforces predictive maintenance as a driver for performance
	Step 3: Incorporate AI in production decision-making	China's Made in China 2025	Enhance real-time decision-making capabilities	AI in manufacturing	Reduced decision time, optimized production processes	Links to AI-driven decision-making for SMEs
	Step 4: Foster a culture of continuous improvement (Kaizen)	Lean Manufacturing Policy Framework	Emphasize ongoing process improvements	Continuous improvement	Increased innovation, reduced waste, improved product quality	Aligns with process optimization for SME growth

Table 19. Cont.

Industry	Roadmap Focus	Policy Framework	Strategic Link	Strategic Drivers	Expected Outcome	Ties to Proposed Study
Healthcare	Step 1: Deploy AI-driven diagnostic tools	European Health Data Space	Improve diagnostics accuracy and reduce costs	AI in healthcare	Improved patient outcomes and reduced diagnostic errors	Supports health tech adoption to improve efficiency
	Step 2: Expand telemedicine capabilities	US SME Policy Act for Healthcare Innovation	Increase healthcare access to underserved populations	Remote healthcare solutions	Greater access to healthcare, improved patient satisfaction	Links telemedicine to improved service delivery
	Step 3: Integrate wearable health monitoring devices		Enable real-time patient monitoring	IoT in healthcare	Continuous health monitoring, timely interventions	Reinforces IoT's role in improving health outcomes
	Step 4: Train healthcare staff in digital tools	EU Health Workforce Skills Policy	Equip healthcare providers with the necessary digital skills	Upskilling and employee training	Enhanced workforce competency, improved patient interactions	Aligns with upskilling to support tech adoption in healthcare
Finance	Step 1: Strengthen cybersecurity measures	Basel III	Ensure data security in digital transactions	Cybersecurity and data protection	Increased trust in financial services, reduced fraud risks	Supports secure fintech integration for SME growth
	Step 2: Adopt blockchain for transaction transparency	African Continental Free Trade Area (AfCFTA) SME Policy	Facilitate secure, transparent transactions	Blockchain in finance	Improved transaction security, increased client trust	Links blockchain to enhanced financial performance
	Step 3: Enhance accessibility to digital finance tools		Promote financial inclusion and access to credit	Digital finance adoption	Increased financial service access for SMEs, improved financial inclusion	Reinforces financial access as a growth driver for SMEs
	Step 4: Integrate AI for risk management		Automate risk assessment and fraud detection	AI in finance	Reduced financial risks, improved decision-making	Aligns with AI-driven innovation in finance

Table 19. Cont.

Industry	Roadmap Focus	Policy Framework	Strategic Link	Strategic Drivers	Expected Outcome	Ties to Proposed Study
Logistics	Step 1: Implement blockchain for supply chain transparency	EU SME Green Deal	Enhance transparency and sustainability in logistics	Blockchain in logistics	Improved visibility, enhanced supply chain transparency	Supports findings on blockchain's role in enhancing supply chain efficiency
	Step 2: Optimize routes using Big Data analytics	US Infrastructure Investment and Jobs Act	Reduce operational costs through efficient route management	Data analytics for logistics	Reduced transportation costs, improved delivery times	Links Big Data to operational efficiency in logistics
	Step 3: Adopt real-time tracking and fleet management systems		Improve asset utilization and tracking capabilities	IoT in logistics	Improved fleet efficiency, reduced downtime	Supports IoT adoption to improve logistics management
	Step 4: Train employees in digital tools for logistics management		Equip logistics workers with digital tools	Upskilling and employee training	Enhanced workforce productivity, improved logistics operations	Reinforces upskilling for digital transformation in logistics

5. Discussion

This paper discusses the importance of Big Data in small and medium-sized enterprises (SMEs) with a focus on key dimensions concerning implications and challenges, as well as one methodological aspect. Analysis shows that Big Data remarkably improve SMEs' performance in business decisions, economic performance, and revenue growth.

RQ1: *How does Big Data capability impact SMEs' performance?*

The research finds that BD capability has a notable impact on SMEs' performance, as shown in Figures 12 and 16. Figure 12 highlights that the most common outcome of BD adoption by SMEs is business improvement (29.03%), achieved through enhanced decision-making and market responsiveness. Economic performance (27.96%) and revenue growth (19.35%) are also key outcomes, underscoring the financial advantages SMEs gain from using BD. While cost savings (16.13%) are acknowledged, SMEs tend to focus more on growth and expansion than on operational cost reduction. Notably, the relatively low emphasis on data-driven innovation (4.30%) and operational efficiency (1.08%) suggests that SMEs may struggle in these areas due to resource constraints or limited expertise. Figure 16 further demonstrates that SMEs account for 73.12% of result variability, indicating their central role in shaping the outcomes of BD initiatives. These findings offer a comprehensive view of how BD capability enhances SME performance, particularly in terms of strategic decision-making, financial growth, and competitive positioning.

RQ2: *What are the critical factors influencing the successful implementation of Big Data on SMEs?*

The critical factors influencing BD implementation in SMEs are examined through Figures 11 and 18. Figure 11 shows that the most common research methods used are surveys (47%) and case studies (28%), each with distinct advantages and limitations. Surveys may introduce self-reporting biases, while case studies provide in-depth insights but lack generalizability. Experimental designs (13%) and quasi-experimental methods (9%) offer causal inferences, but struggle with external validity. The scarcity of quantitative methods (1%) and document analysis (2%) further emphasizes the need for diverse research approaches to capture the full range of factors affecting BD implementation. Additionally, Figure 18 reveals a reporting bias toward quantitative studies, with fewer qualitative and mixed-method studies. Addressing this imbalance and utilizing a broader range of research methods can improve understanding of the factors that drive or hinder successful BD adoption in SMEs.

RQ3: *How can awareness and understanding of Big Data be leveraged to enhance productivity in SMEs?*

Awareness and understanding of BD are crucial for leveraging their full potential in SMEs, as highlighted in Figures 10 and 17. Figure 10 shows that countries such as China and Italy have seen a growing recognition of BD's benefits, reflected in increased research activity. This heightened awareness has contributed to productivity improvements by encouraging the adoption of BD tools. Figure 17 highlights the prominence of data mining (26.88%) and predictive analytic (16.13%) techniques, which are essential for refining decision models and ensuring accurate insights. By deepening their understanding of BD capabilities, SMEs can make more informed decisions and optimize operational efficiency, ultimately driving productivity growth.

RQ4: *What are the challenges SMEs face in integrating Big Data into their existing systems and operations?*

The challenges SMEs encounter when integrating BD into their existing systems and operations are highlighted in Figures 8 and 14. Figure 8 shows that a majority (63.44%) of research papers on this topic are sourced from Google Scholar, reflecting the broad scope of challenges across diverse contexts. Figure 14 focuses on the methods used for data collection, revealing that document analysis (36.56%) and interviews (33.33%) provide

valuable qualitative insights into the obstacles SMEs face. These challenges include resource limitations, technical difficulties, and issues with integrating BD into existing infrastructure. This methodological focus underscores the importance of understanding these barriers to help SMEs navigate the complexities of BD implementation.

RQ5: *How can SMEs effectively adapt their decision-making processes to harness the full potential of Big Data analytics?*

SMEs can adapt their decision-making processes by adopting a more data-driven approach that allows them to harness the full potential of BD analytics. The findings in Figures 12 and 16 emphasize that SMEs often prioritize business improvement and growth, but there is significant untapped potential in areas such as operational efficiency and innovation. By integrating advanced analytical techniques like data mining and predictive analytics (Figure 17) into their decision-making processes, SMEs can not only improve performance outcomes but also foster greater innovation and competitiveness. A shift towards data-driven decision-making will enable SMEs to unlock the full benefits of BD and better align their strategies with market demands.

6. Conclusions

This systematic review reveals that Big Data offer significant benefits for small and medium-sized enterprises (SMEs), including improved decision-making, enhanced operational efficiency, and revenue growth. However, the review also identifies significant barriers to adoption, such as financial constraints, limited technical expertise, and inadequate organizational readiness. These challenges must be addressed for SMEs to fully leverage Big Data's potential. The key practical implication is that Big Data adoption can drive competitiveness and innovation, but SMEs must invest in appropriate financial resources, develop technical skills, and ensure alignment between Big Data initiatives and core business objectives.

To address these barriers, SMEs should prioritize building a culture of data-driven decision-making, supported by leadership and organizational commitment. Enhancing data literacy across teams and breaking down organizational inertia are essential to successful integration. Creating a strategic roadmap that links Big Data capabilities with specific business goals will help SMEs maximize their return on investment. Industry leaders and policymakers can play a crucial role by offering tailored support frameworks that include access to funding, training programs, and infrastructure designed to meet the unique needs of SMEs. Specific recommendations for researchers include conducting more empirical studies and practical case analyses, particularly focusing on underexplored regions such as developing economies. Future research should aim to provide actionable insights and practical examples that demonstrate how SMEs can overcome barriers and successfully implement Big Data. The review highlights the importance of aligning Big Data adoption with strategic business objectives, investing in technical training, and fostering an organization-wide commitment to data-driven innovation. These steps are crucial for ensuring that SMEs not only adopt Big Data but also use them effectively to achieve sustainable growth and improved performance.

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