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Acquiring Knowledge from Big Data in the Digital Age: A Systematic Literature Review

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ABSTRACT

Big Data has become a critical driver of innovation and competitiveness, yet many organizations continue to struggle to transform data into actionable knowledge. This challenge persists because firms lack clarity on the critical resources and integrated processes required to effectively acquire and apply knowledge from Big Data. This study conducts a PRISMA-guided systematic literature review to synthesize how firms acquire knowledge from Big Data, the resources that enable this capability, and how the resulting knowledge enhances decision quality. The findings reveal that Big Data knowledge acquisition operates through a three-stage cycle, data integration, analytical knowledge generation, and organizational absorption and application, supported by six interdependent resource dimensions: technology, human, data, organization, knowledge, and environment. Each dimension plays a distinct but complementary role in enabling firms to capture, integrate, and transform Big Data into meaningful knowledge. The study identifies actionable patterns that demonstrate how these resources can be configured to strengthen evidence-based decision-making, strategic foresight, innovation, and continuous learning. By clarifying the dynamic interplay between methods, processes, and resources, this study provides both theoretical insights and practical guidance for organizations seeking to develop sustainable data-driven capabilities.

1. Introduction

In a world where digital technologies are found in nearly every aspect of life, data has grown to become one of the most valuable resources, especially for individuals and organizations that are seeking growth and improvement. Every digital interaction, whether by scrolling through social media, using online services, or connecting through smart devices, contributes to an ever-growing stream of information produced across sectors worldwide [1][2]. Recent estimates suggest that approximately 402.74 million terabytes of data are generated worldwide each day. Global data growth projections further indicate that by 2025, the total volume of data generated is expected to reach 181 zettabytes, an increase from the estimated 147 zettabytes recorded in 2024 [3]. This continuous generation of data has given rise to what is known as “big data”, massive datasets that, when analyzed together with advanced techniques, reshape how knowledge is created, shared, and applied.

Although massive amounts of data are being generated continuously, raw data hold little value until they are transformed, analyzed, and interpreted to generate knowledge. As the size of big data increases, simply collecting information becomes insufficient. Organizations must be able to identify patterns, extract relevant information, and interpret results in a way that creates actionable business insights for value [4]. These

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processes allow data to move beyond numbers and become meaningful assets that guide decision-making, drive innovation, and support long-term growth [5].

Despite its potential, many organizations continue to face significant challenges in fully harnessing the value of big data [6]. A recent empirical study by [7] involving organizational surveys, interviews, and case studies revealed that 60% of the participating organizations faced shortages of skilled data scientists and analysts, 45% noted resistance in building a data-driven culture, and 50% reported difficulties in integrating big data technologies with existing systems. A shortage of skilled personnel, high implementation costs, and technical complexity often limit organizations ability to adopt big data analytics effectively. Furthermore, despite advances in big data technologies, the adoption of modern database systems remains limited across organizations [8]. In addition, organizational resistance to change often slows the integration of new technologies, leaving firms unable to fully capture the benefits of their data resources. These barriers highlight the gap between the growing availability of big data and firms ability to use it effectively [9].

Prior studies have emphasized that firms require a combination of skilled personnel, analytical tools, and robust data management practices to effectively acquire knowledge from big data [10]. They also highlight that knowledge-sharing processes can support better decision-making, but their impact depends on the strength of a firm’s analytical capabilities and the presence of technological, cultural, and organizational enablers that support collaboration and trust [11][12]. Although these resources have been examined individually, there remains a limited understanding of how they interact in practice and how firms can cohesively manage them to create effective knowledge-acquisition processes.

Moreover, the existing literature lacks an evidence-based explanation of how firms combine and sequence different resources to build scalable and repeatable knowledge-acquisition processes. Consequently, organizations invest in analytics technologies without achieving meaningful business outcomes, revealing both practical and theoretical gaps. This study addresses this gap by conducting a systematic literature review of knowledge acquisition from big data in the digital age. Beyond synthesis, this review integrates findings into a coherent explanation of how knowledge acquisition methods interact with the critical resources that enable them and how data-driven knowledge can be strategically applied to gain organizational advantages. This study also proposes a set of actionable guidelines for firms that highlight the specific resources that support the effective use of data-analytics tools. By systematically synthesizing and interpreting recent research, this study bridges theoretical understanding with managerial applications, offering both conceptual and practical roadmaps for strengthening data-driven decision-making and innovation.

The research was guided by the following three questions:
RQ 1. What methods, processes, or approaches do firms use to acquire knowledge from big data?
RQ 2. What are the critical resources that firms need to implement these processes to acquire knowledge from big data effectively?
RQ 3. How can firms leverage the knowledge acquired from big data to enhance decision quality and achieve data-driven strategies?

2. Research Method

This research adopts a Systematic Literature Review (SLR) conducted following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A comprehensive search was performed across electronic databases, including Google Scholar, Emerald, ScienceDirect and IEEE Xplore, using relevant keywords such as “big data”, “big data analytics”, “knowledge acquisition”, “firms”, and “critical resources”. Boolean operators (AND, OR, NOT) were applied to refine the results and effectively

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link related concepts. For example, queries such as ("big data" AND "knowledge acquisition" AND “firms”) were used to expand coverage while filtering out irrelevant studies.

Research Flow

The research flow in this study was structured to ensure transparency and rigor throughout the whole process. It began by defining the research questions to establish a clear scope, followed by a comprehensive literature search across selected databases. The identified studies were then screened through title and abstract review, duplicates were removed, and full texts were assessed to ensure alignment with the research objectives. Eligible studies were subjected to a quality assessment to ensure that only robust and relevant studies were retained. Key data were systematically extracted using a structured template and synthesized to identify recurring themes, patterns, and insights. The findings were subsequently organized and integrated into the systematic literature review, providing a structured foundation to address the research questions.

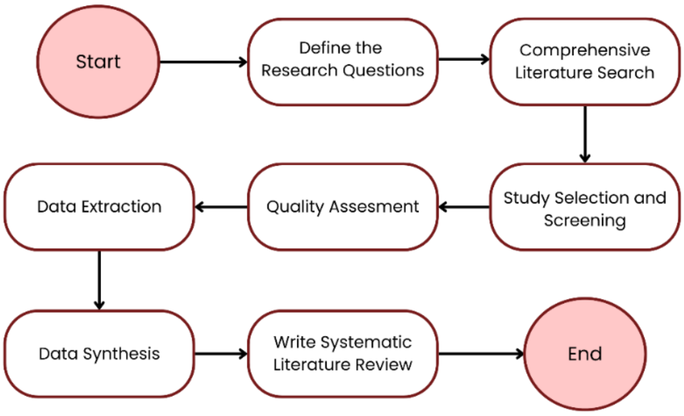

Figure 1. Research Flow

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were applied to ensure that only studies directly relevant to the objectives of this research were selected. Articles were included if they were published between 2020 and 2025, appeared in peer-reviewed journals, and explicitly focused on big data, big data analytics, or related organizational practices. Studies that did not meet these conditions, such as non-peer-reviewed works or publications unrelated to big data, were excluded. By setting clear boundaries, this review concentrated on recent, empirically grounded studies, strengthening the reliability of the findings, and ensuring that the analysis reflects current developments.

Table 1. Inclusion and Exclusion Criteria

Inclusion	Exclusion
Studies published between 2020–2025	Studies published before 2020
Peer-reviewed journal articles	Non-peer-reviewed works
Studies addressing big data, big data analytics, or knowledge acquisition in firms	Studies not related to big data or big data analytics in organizational contexts
Publication written in English	Publication written in languages other than English
Full-text availability	Abstract only or inaccessible studies

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Empirical research, literature review, case studies and systematic reviews	Conceptual or theoretical works without empirical or applied evidence

Following the application of these criteria, all selected studies underwent a structured quality assessment to ensure the reliability and credibility of the findings. This process was designed to evaluate the relevance of each article to the research objectives of this study. The assessment focused on several key aspects, including the publication period, clarity in describing methods and processes, specification of critical resources, and practical insights into how firms utilize these resources. Each study was examined against predefined criteria and assigned a score of *Yes (Y)* if it met the requirement or *No (N)* if it did not meet the requirement. This scoring approach provides a transparent framework for comparing studies and determining their suitability for inclusion in the review.

Table 2. Paper Quality Assessment

Criteria	Scoring
Published between 2020–2025	**Y/N**
Describes methods, processes or approaches used by firms to acquire knowledge	**Y/N**
Specifies the critical resources required for big data analytics	**Y/N**
Provides insights into how firms manage and leverage the knowledge acquired	**Y/N**

Data Collection Process

The data collection process involves systematic gathering of primary and secondary sources to ensure comprehensive coverage of the relevant literature. The primary data consisted of peer-reviewed journal articles retrieved from widely recognized databases, while secondary data were incorporated to provide additional context and strengthen the interpretation of the findings. Sources included peer-reviewed journal articles, empirical research, case studies, and systematic reviews conducted by other researchers, offering valuable insights into broader trends, empirical findings, and practical applications of big data and analytics across industries. The combination of primary and secondary data enabled a more balanced and nuanced understanding of the research problem.

To maintain consistency and organization, all collected references were stored and managed using Mendeley, a digital reference management tool. This platform allowed for the systematic storage, retrieval, and citation of articles, reducing redundancy and ensuring accuracy in the review process. By consolidating data in a centralized system, the researcher minimized the risk of overlooking relevant studies and ensured transparency in the selection process. Once the relevant studies were collected and organized, the next stage involved data analysis to ensure that the findings directly addressed the research objectives of this study. This structured approach ensured that the analysis was rigorous, comprehensive, and closely aligned with the research questions.

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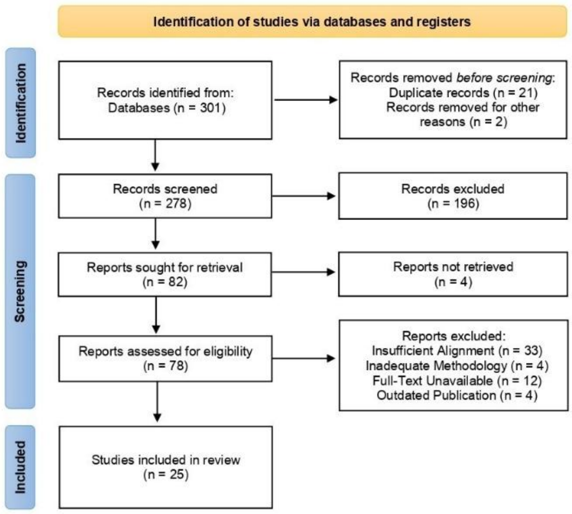

Figure 2. PRISMA Flow Diagram

The systematic selection of studies was further documented using the PRISMA flow diagram. This process began with 301 records that were identified across databases. After removing 21 duplicate records and 2 records for other reasons, 278 unique records remained for screening. Following title and abstract screening, 196 records were excluded, and 82 studies were selected for retrieval. Out of these, 4 reports could not be retrieved in full, resulting in 78 studies assessed for eligibility. During the eligibility assessment, 33 studies were excluded due to insufficient alignment with the research objectives, 4 due to inadequate methodology, 12 due to full-text unavailability, and 4 because of outdated publications. This resulted in a final set of 25 studies that were included and formed the basis for the review.

Data Analysis and Synthesis

Once the studies were selected and the key information was extracted, the next step was to analyze and bring the findings together. This process was carried out using thematic synthesis, which focused on identifying recurring patterns and themes related to knowledge acquisition from big data. Through this approach, the analysis highlighted the key actions and strategic choices that consistently appeared across studies, allowing a clearer understanding of how organizations leverage big data for knowledge creation and decision-making. This ensured that the findings were coherent, relevant, and directly aligned with the research objectives.

3. Result

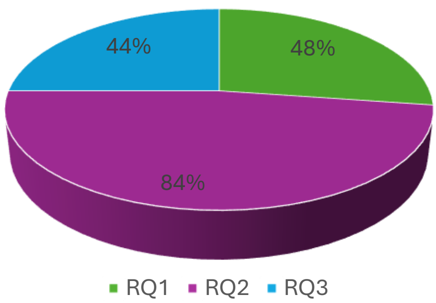

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Figure 3. Percentage of Reviewed Studies Addressing Each Research Question

Figure 3 displays the percentage of the 25 reviewed studies that address each research question. The majority of the studies, 21 papers (84%) addressed the critical resources required for effective big data knowledge acquisition (RQ2), followed by 12 papers (48%) that examined the methods, processes, or analytical approaches and (RQ1) and 11 papers (44%) that discussed the application of knowledge for strategic outcomes (RQ3). Overlap occurs when some studies simultaneously address more than one research question. To address the research questions in greater depth, the following sections examine how the reviewed studies collectively respond to each research question.

RQ 1. What methods, processes, or approaches do firms use to acquire knowledge from big data?

Table 3. Methods Used by Firms to Acquire Knowledge from Big Data

Knowledge Acquisition Method	Key Methods Identified	Description	Citation
Data Mining & Analytics	- Clustering Analysis - Classification Models - Descriptive/Trend Analysis - Association Rule Analysis - Data Visualization	Extraction of patterns, relationships and insights from large datasets to identify trends, understand behaviors and anticipate future outcomes.	[13], [14], [15], [16]
Artificial Intelligence (AI) & Machine Learning	**Supervised Learning** - Neural Networks / Deep Learning - Predictive Modeling (Regression, Decision Trees) - Classification Models - Forecasting Models - Predictive Scoring Models - Pattern Recognition **Unsupervised Learning** - Clustering - Anomaly/Pattern Detection (Unlabeled Data)	Application of ML and AI algorithms to derive predictive and diagnostic knowledge from historical and sensor data. Supervised learning forecast outcomes and classify entities while unsupervised methods discover latent patterns or anomalies for continuous learning and optimization.	[13], [14], [16]
Analytical Data Integration & Visualization	- Integrated Data Consolidation with Data Warehousing - Analytical Data Processing through BI Platforms (SAS, IBM Cognos) - Dashboard Analytics - Interactive Data Communication & Visualization	Integration and transformation of large, multi-source datasets into centralized data warehouses, followed by analytical processing and visualization through Business Intelligence (BI) platforms towards visualization.	[14], [17]

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In an era defined by information abundance, firms are increasingly seeking structured approaches to transform data into meaningful knowledge. To achieve this advanced capability, a range of analytical and technological methods designed to capture, process, and interpret information at large scales have been employed [16]. Among the reviewed studies, four discussed data mining and analytics techniques, three employed machine learning or artificial intelligence systems, and one utilized business intelligence or data warehousing tools. Together, these findings indicate that firms rely heavily on algorithmic and analytical approaches to derive insights from big data, with traditional BI systems playing a more limited but complementary role in data integration and data presentation.

Analytical exploration approach allows organizations to delve deeper beyond surface level information, revealing the interconnections that influence customer behavior, operational efficiency, and market dynamics. As analytical capabilities advance, firms are increasingly adopting advanced data-driven tools such as artificial intelligence (AI) and machine learning [13]. By translating raw data into insights through these technologies, firms gain an evidence-based understanding that strengthens both strategic and operational decision-making [15].

Equally important is the integration of diverse data sources into centralized systems that allow for collective interpretation and visualization. Through data consolidation and the use of analytical environments that present information visually, managers can observe patterns, monitor performance, and explore scenarios in real time. These integrative and interpretive processes empower firms to recognize dependencies, turning analytical outputs into actionable knowledge [14][17]. Ultimately, as these analytical and technological practices converge, they form the foundation for firms to acquire and refine knowledge continuously. Insights generated from repeated analyses, modeling, and visualization are integral components of strategic and operational routines, ensuring that knowledge remains actionable [14].

Table 4. Processes and Approaches for Knowledge Acquisition from Big Data

Process/Approach Themes	Description	Contribution to Knowledge Acquisition	Citation
Data Resource Integration and Knowledge Creation	Integration and synthesis of multiple internal and external data sources (e.g. IoT, ERP, customers) to recognize patterns, correlations, and emerging trends across systems.	Enables the discovery of relationships and dependencies across diverse datasets, fostering cross-functional information. This process transforms fragmented data into coherent and actionable organizational knowledge.	[14], [18]
Data Processing and Analytical Knowledge Extraction	Utilization of algorithms, tools, and mechanisms to aggregate, analyze, refine, and visualize Big Data.	Transform and refine raw data into structured and interpretable insights, enabling the conversion of information into actionable knowledge.	[17], [18], [19]
Strategic Capability Development for Knowledge Acquisition	Establishment and alignment of capabilities that enable firms to effectively capture, interpret, and utilize knowledge derived from Big Data.	Enhance firm's capacity by developing the necessary technical infrastructure, analytical skills, and managerial coordination that enable continuous data collection, processing, and interpretation. Ensuring the ability to generate knowledge from Big Data in a structured and scalable manner.	[20], [21], [22]

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Iterative Learning and Knowledge Refinement Cycles	Iterative processes in which data is analyzed, interpreted, and re-applied through feedback-driven refinement loops and contextual learning.	Facilitate continuous organizational learning and knowledge evolution by embedding analytical outcomes into organization routines, enabling firms to continuously adapt and expand their knowledge base through experiential learning.	[14], [16], [23]

Integrating information from various internal and external sources allows firms to capture and gain a more comprehensive understanding of their operations and environment. By connecting data from various systems, firms can uncover hidden patterns and interdependencies that remain invisible when sources are examined separately. This integrative process forms the analytical foundation for knowledge creation, as diverse datasets are interpreted and analyzed, often supported by cross-department collaboration to transform dispersed and fragmented information into structured insights [18].

Firms increasingly rely on systematic and technology-driven processes to transform vast and complex datasets into forms that can be interpreted and applied meaningfully. By utilizing advanced analytic infrastructures, data are aggregated, analyzed, and visualized using algorithms and analytical tools to uncover patterns that inform strategic and operational decisions. This process enables raw information to evolve into structured insights, which leads to the creation of actionable knowledge across business contexts [19].

Beyond technology, they must also strengthen their capabilities to manage and interpret information effectively by developing a stronger capacity to sense, contextualize, and respond to insights [20]. Through the gradual enhancement of these internal capabilities, organizations transition toward structured, knowledge-driven operations, ensuring that insights derived from Big Data are consistently transformed into meaningful organizational learning [21][22].

Finally, iterative learning cycles allow data to be continuously analyzed, interpreted, and reapplied across different stages of decision-making. Through ongoing feedback and refinement, insights derived from analytics become embedded within organizational practices, allowing knowledge to evolve dynamically in response to experience and environmental changes. This continual adaptation process enables firms to internalize data-driven understanding, fostering sustained learning and the progressive expansion of organizational knowledge over time [23].

RQ 2. What are the critical resources that firms need to implement these processes to acquire knowledge from big data effectively?

Table 5. Critical Resources for Effective Big Data Acquisition

Category	Mentioned Critical Resources	Citation

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Technology	1. Data Processing Technologies & Advanced Analytical Tools 2. Cloud Computing 3. Storage Platforms 4. System Connectivity, Compatibility & Modularity 5. Data Integration & Management Systems 6. Data Acquisition & Aggregation Technique 7. Artificial Intelligence (AI) Algorithms 8. Visualization Tools 9. IT Architecture for Real Time Analytics 10. End User Oriented Software 11. End User Oriented Development Tools	1. [13], [16], [18], [24], [25], [26], [27], [28], [29], [30], [31], [32] 2. [13], [14], [18], [33], [25] 3. [13], [14], [18], [25], [29], [31] 4. [13], [33], [28], [29], [31] 5. [16], [24], [27], [32], [34] 6. [18] 7. [18] 8. [18], [29], [31] 9. [28] 10. [14], [35] 11. [14]
Human	1. Skilled Personnel with Technical and Analytical Proficiency 2. Business & Relational Understanding 3. Expert Teams Combining Domain Capabilities & Technical Skills to Interpret Data 4. Cross Functional Collaboration Among Teams 5. Continuous Personnel Skills Training & Development in Data Literacy 6. Ability to Interpret & Communicate Analysis 7. Entrepreneurial Orientation 8. Managerial Decision Making Capabilities	1. [13], [15], [16], [18], [33], [20], [21], [23], [24], [25], [28], [29], [30], [32], [34], [35] 2. [13], [14], [33], [29] 3. [15], [21], [24] 4. [24], [28], [29], [31] 5. [15], [26], [28], [31], [36] 6. [14], [18], [27] 7. [21] 8. [21], [31], [34]
Data	1. Quality Data & Governance 2. Data Management & Storage Capability 3. Data Accessibility & Sharing 4. Heterogeneous Data Sources Integration 5. Data Generation & Understanding 6. Real Time Data Access 7. Customer Generated Data 8. High Volume, Variety & Velocity of Data	1. [13], [14], [15], [18], [22], [23], [25], [29], [31], [32], [35] 2. [13] 3. [13], [22], [29], [36] 4. [13], [14], [18], [25], [29], [31] 5. [14], [18] 6. [14], [18], [22], [34] 7. [20], [30] 8. [21]
Organization	1. Management Capability (Planning, Investment, Coordination) 2. Managerial Control & Governance Structures for Data Use 3. Strategic Leadership 4. Top Managerial Support 5. Management Commitment & Strategic Coordination 6. Strategic Business Alignment Capability on Big Data 7. Monitoring Towards Continuous Innovation 8. Data Driven Culture & Digital Mindset within Organization 9. Flexible Organizational Structure for Experimentation 10. Dynamic Capability Orchestration 11. Supply Chain Integration	1. [13], [33], [20], [25] 2. [13], [14], [33], [25], [26], [27], [28], [31], [35] 3. [14], [20], [24], [26] 4. [20], [23], [25], [36] 5. [26] 6. [14], [15], [22], [27], [31], [36] 7. [18], [31] 8. [20], [27], [28], [34] 9. [14], [28] 10. [21], [29], [34] 11. [34]
Knowledge	1. Knowledge Integration & Sharing Mechanisms 2. Continuous Learning Routines & Absorptive Capacity 3. Insights Integration with Decision Process 4. Technology Management Knowledge 5. Knowledge Management Capability	1. [13], [16], [18], [24], [25], [29], [35], [36] 2. [13], [20], [23], [24], [25], [29] 3. [18] 4. [33], [29], [35] 5. [16], [32]

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Environment	1. Collaboration & Data Sharing Ecosystems 2. Environmental Adaptability & Responsiveness 3. Organizational Agility Towards Resources 4. Regulatory & Market Environment	1. [13], [14], [15], [23], [24] [25], [36] 2. [13], [14], [24], [29] 3. [36] 4. [14], [16], [29], [32]

The ability of firms to acquire and utilize knowledge from big data effectively depends on the availability and integration of several critical resources [13], each of which represents a core area of capability that supports the implementation of methods, processes, and approaches for knowledge acquisition. From the 22 reviewed papers that addressed this research question, six key resource dimensions were identified: technology, human, data, organization, knowledge, and environment. Human resources were the most frequently emphasized, appearing in 21 papers, followed by organizational resources discussed in 18 papers.

Technology and data were mentioned in 16 papers, highlighting their significance in supporting analytical and operational capabilities. Knowledge-related resources appeared in 12 papers, while environmental factors were identified in 10 papers. Overall, these findings indicate that firms place greater emphasis on human and organizational capabilities, recognizing them as critical enablers of big data knowledge acquisition.

TECHNOLOGY

Technology refers to the infrastructure and tools required to conduct big data analytics, allowing firms to effectively capture, store, manage, and process massive volumes of data. It involves the integration of various technological applications and systems that work together to generate meaningful value and address a firm's operational shortcomings [13]. When firms generate large amounts of data that must be processed rapidly, technology becomes particularly valuable in ensuring smooth data processing and reducing the risk of interruptions in knowledge acquisition. Well-developed technological resources provide firms with new opportunities to transform their business practices and respond more effectively to market needs [29].

HUMAN

Human resources play an enabling role in acquiring and utilizing knowledge from big data, as its implementation is meaningless without the presence of skilled experts who can manage, interpret, and apply data effectively [23]. As highlighted in [27], focusing on human technical and managerial skills is crucial, since processes towards innovation often depend on strong, domain-specific expertise. They are essential not only for interpreting analytical outputs but also for extracting, organizing, and applying data, which rely heavily on human technical excellence and skill to generate business value. This emphasizes the importance of human knowledge of digitalization and analytical capabilities as a critical resource that enables firms to realize the full potential of big data [16].

DATA

As an essential elements, data serve as raw material for generating, processing, and applying insights from big data initiatives to acquire knowledge. Firms must ensure that their data are accurate, relevant, and accessible because data quality, consistency, and availability are crucial components of effective data capabilities [13]. Data were gathered from multiple structured and unstructured sources. To fully harness the potential of such vast data flows, data governance must be deeply embedded within the organization to ensure proper management and strategic alignment with the firm's objectives [18].

ORGANIZATION

Organizational resources determine how effectively a firm can align its structure, culture, and processes to support big data initiatives [20]. An organization's capabilities form the foundation for effective

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coordination and strategic alignment across business functions, ensuring that data-driven activities contribute to overall organizational goals [22]. Clear governance, strategic leadership, and commitment from management foster accountability and direction in utilizing big data. These resources, when combined with a flexible structure and adaptive culture, enable firms to experiment, learn, and continuously improve through big data insights [24].

KNOWLEDGE

Knowledge resources encompass the expertise and intellectual assets that enable firms to interpret, integrate, and apply data insights. Through effective knowledge management and continuous learning, firms combine new insights with past experiences and apply them in decision-making, leading to a better understanding of their environment. By effectively sharing and storing knowledge across the organization, firms can prevent redundancy, support responsible data handling, and foster continuous learning [13]. In

essence, these capabilities allow firms to continuously refine their understanding, strengthen data-driven decision-making, and sustain innovation through accumulated learning.

ENVIROMENT

The environmental dimension shapes how firms acquire and utilize knowledge from big data by influencing opportunities, constraints, and competitive pressures. A supportive ecosystem that promotes collaboration and data sharing enhances access to knowledge and technological opportunities. Regulatory policies, technological trends, and market dynamics all affect how data is accessed and analyzed, while the ability to adapt to these external forces allow firms to remain responsive and agile in pursuing digital transformation. Firms that remain responsive to environmental changes can better translate external signals into strategic knowledge-based advantages [36].

RQ 3. How can firms leverage the knowledge acquired from big data to enhance decision quality and achieve data-driven strategies?

Table 6. Leveraging Knowledge for Decision Making and Strategic Outcomes

Leveraging Knowledge Area	Strategic Outcomes/Benefits	Citation
Strategic Foresight & Market Sensing	Analytics generated knowledge helps firms detect market trends and anticipate customer or competitor movements, strengthening long-term strategic planning and agility.	[18], [30], [32], [35]
Knowledge Driven Sustainable Performance	Knowledge leveraged by transforming the analytical insights into organizational understanding of internal processes and environments, embedding it into policies and strategies to align financial, environmental, and social goals, enhancing sustainable performance and competitiveness.	[26]
Evidence Based Managerial Decision-Making	Firms embed analytics insights into daily decision routines, replacing organization intuition with measurable and judgments supported data, improving accuracy, consistency, and overall decision quality.	[23], [36]

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Innovation, Improvement & New Value Creation	Knowledge extracted from Big Data uncovers performance gaps and emerging opportunities, guiding products/services redesign and the development of new business models or practices that strengthen and sustain competitive advantage.	[18], [21], [24], [28], [30], [37]
Real Time Responsiveness & Operational Excellence	Continuous analytic feedback improves operational control, resource allocation, and agility, shortening decision cycles and reducing costs.	[23]
Strategic Agility & Reconfiguration	Data driven knowledge enables dynamic adjustment to reconfigure and redeploy internal and external resources in response to digital transformation, fostering adaptive strategies under volatility. Sustaining competitive advantage by aligning capabilities with changing digital environments.	[24], [28], [35], [36]
Continuous Learning & Knowledge Institutionalization	Knowledge derived from analytics is fed back into organizational learning systems, improving future decision quality and innovation cycles.	[23], [36]

Through systematic methods and organizational support, firms can extract and transform big data into actionable knowledge that drives informed decision-making and performance improvement. The effective use of such knowledge strengthens both the quality of managerial decisions and the firm’s ability to achieve data-driven strategic outcomes [36].

The ability to convert knowledge generated from big data into strategic intelligence enables firms to anticipate market changes, detect evolving consumer needs and monitor competitor behavior with precision. It allows organizations to sense subtle shifts that might otherwise go unnoticed, allowing timely strategic adjustments towards long-term planning and resilience [18]. By continually interpreting performance data and external trends, firms can adapt by dynamically reconfiguring and redeploying resources amid digital transformation and market volatility, turning environmental change into a strategic advantage [28].

Firms also embed knowledge into managerial routines, enabling decision-making that moves beyond intuition and personal bias, instead relying on objective, evidence-based insights. When decision-makers are guided by verifiable knowledge, their choices become more consistent, transparent, and aligned with organizational goals [36]. This approach enhances managerial confidence and accountability because the outcomes can be measured and evaluated against empirical benchmarks. This ultimately improves the accuracy, credibility, and effectiveness of decisions across organizations.

Knowledge derived from big data also plays a pivotal role in driving innovation and creating value. By revealing performance gaps, shifting customer preferences, and untapped market segments, such knowledge serves as a guide for product redesign, service improvement, and business model transformation [18]. This data-driven approach enables firms to innovate with precision, focusing resources on generating the greatest strategic impact. Over time, fostering a culture of continuous improvement and experimentation helps organizations remain relevant, competitive, and capable of sustaining innovation in dynamic markets [24].

Continuous feedback from data-driven systems enables firms to accelerate decision cycles and optimize resource utilization across operations. With access to real-time insights, managers can monitor key performance indicators, detect inefficiencies, and implement timely adjustments to processes or resource allocations. This responsiveness enhances operational agility, service quality, and customer satisfaction, while also contributing to superior cost control and increased adaptability [23]. As institutionalized knowledge strengthens decision quality, fosters continuous innovation, and enhances strategic agility, it ensure that firms remain competitive and resilient in dynamic environments [36].

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4. Discussion

The findings of this systematic literature review show that acquiring knowledge from big data is not a single analytical step but a multistage, resource-dependent process that emerges consistently across the studies analyzed. Integrating insights from the reviewed studies reveals that firms acquire knowledge through a three-stage cycle: (1) data integration, (2) analytical knowledge generation, and (3) organizational absorption and application. This three-stage pattern was not predetermined but emerged from the data found during the thematic synthesis of the methods, resource dependencies, and strategic outcomes repeatedly reported across the included studies.

The first stage, data integration, captures how firms consolidate heterogeneous data, including IoT, ERP, customer interactions, social media content, and external market signals, into coherent analytical environments. While individual studies emphasize infrastructure, such as data warehouses, cloud platforms, and integration systems [14], the synthesis reveals that integration becomes meaningful only when supported by human and organizational routines that determine relevance, ensure data quality, and align data choices with strategic priorities [18]. These findings suggest that firms strengthen their knowledge acquisition when they establish clear data governance structures and routine mechanisms to validate and prioritize data inputs, ensuring that technological resources and human judgment cooperate [22]. Thus, data integration is not purely a technical task but a socio-technical knowledge activity shaped by data resources, human expertise, and organizational processes. This pattern has been reported in studies. For instance, research in the hospitality sector showed that hotels could not fully benefit from integrated guest-generated data until data governance routines and cross-departmental coordination were established, illustrating that technical integration only creates value when combined with dynamic capabilities such as human, organizational practices, and data-driven culture at a strategic and operational level [20].

The second stage, analytical knowledge generation, emerges from studies that describe data mining, predictive modeling, deep learning, clustering, and statistical techniques. While publications often emphasize tool sophistication, the synthesis shows that analytical tools alone are insufficient for generating strategic knowledge, as their effectiveness consistently depends on human resources, such as data literacy, domain expertise, and interpretive skills, as well as organizational resources, including collaborative workflows and governance routines [16]. These patterns indicate that firms improve knowledge generation only when they cultivate organization-wide data literacy, develop employees' analytical and domain competencies, and create cross-functional structures that enable the shared interpretation of analytical outputs [24]. Thus, analytical knowledge arises not from tools in isolation but from their coordinated interactions with people, organizational mechanisms, and high-quality data inputs. This alignment was also visible in manufacturing firms, where predictive analytics improved performance only when supported by employee analytical skills and domain expertise, demonstrating that human and organizational resources are indispensable for transforming analytics outputs into meaningful insights [18][25].

The third stage, organizational absorption and application, was less developed in individual studies but became clearer when the evidence was synthesized. Studies have reported cases in which insights were generated but not used, revealing persistent bottlenecks. The review shows that insights become actionable knowledge only when embedded into routines [20] and shaped by organizational practices such as knowledge integration and learning processes through which firms interpret and act on analytical outputs [18]. Environmental dynamism, such as rapidly changing markets, plays a part in shaping how firms use analytical knowledge and how quickly they respond to new information [29]. These patterns reveal that firms enhance the application of insights when they formalize knowledge-sharing routines, integrate analytics outputs into decision workflows, and develop learning mechanisms that allow insights to be revisited, refined, and translated into operational changes [13]. This addresses the fundamental challenge identified in the literature by closing the gap between producing insights and strategically using them. The importance of these routines

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is also reflected in SMEs, where firms that implement structured knowledge-sharing mechanisms are more capable of converting analytical insights into operational improvements and innovative outcomes [14].

Together, these stages illustrate how knowledge acquisition from big data emerges through the coordinated interaction of critical resources. Instead of treating technological, human, organizational, data, knowledge, and environmental resources as isolated categories, this review demonstrates that knowledge acquisition occurs through their interactions. Technologies process data, but humans interpret them, organizational structures enable collaboration, knowledge resources determine how new insights connect with existing understanding, and environmental conditions influence data availability, urgency, and strategic relevance [13]. This interdependence appeared consistently across industries represented in the reviewed studies, including retail, construction, manufacturing, and financial services, highlighting how firms can leverage these processes and resources to achieve improved performance.

The synthesis also reveals patterns that clarify how firms can build the resource configurations required for effective knowledge acquisition. Across studies, organizations have achieved more robust outcomes when they assembled cross-functional analytics teams, allowing technical specialists, domain experts, and decision-makers to collectively interpret and ensure strategic fit [15]. Several studies showed that knowledge acquisition was strengthened when firms develop structured strategies, strong governance, and reliable data infrastructure, firms often need to establish these basics before more advanced analytical tools could deliver value [31]. Evidence also shows that firms benefit from treating analytics as a continuous learning cycle, in which they enhance and adjust their capabilities over time as they gain new experience and understanding in response to environmental changes and new organizational knowledge [13]. These subtle yet consistent patterns emphasize that successful knowledge acquisition requires not only advanced analytics but also the coordinated, sequenced, and sustained development of the critical resources that enable them.

This synthesis aligns with and extends prior literature. For example, study [38] demonstrated that Big Data functions as a strategic knowledge resource that enhances firms' strategic decision quality when analytical techniques are combined with cognitive and organizational capabilities. The study further indicates that diverse combinations of resources related to big data play a critical role, especially in organizational cognitive characteristics and managerial skills. Similarly, [39] emphasize that Big Data Analytics Capability (BDAC) represents a strategic organizational capability that transforms raw data into actionable insights through the integration of technological, human, and organizational resources, since the value of Big Data lies in a firm's ability to interpret and apply data effectively rather than merely possessing analytical tools. Extending to this perspective, [40] demonstrated the process of leveraging big data by embedding predictive intelligence into business operations and supported the view of the knowledge acquisition process by converting fragmented data into interpretable insights. However, findings from [41] present a contrasting perspective, indicating that the use of Big Data does not always enhance decision quality. When organizations face cognitive overload, poor data culture, or knowledge-hiding behaviors, the analytical process can overwhelm decision-makers and reduce insight clarity. This suggests that the benefits of Big Data depend heavily on the organizational environment, while it can strengthen knowledge acquisition under supportive conditions, it may also hinder the overall decision quality and outcomes as firms continue to struggle with data complexity.

The final pattern that emerged across the reviewed studies concerns how the knowledge produced through analytics translates into improved decision quality. Although many studies report gains in accuracy, responsiveness, and strategic alignment, the synthesis shows that such improvements occur only when analytical insights are embedded into decision structures that are timely, interpretable, and actionable. Studies show that marketing departments strengthen data-driven decision-making when they establish formal routines and mechanisms that ensure analytics insights are delivered to managers in a usable form and at the points in the process where decisions are made [23]. Research in the hotel industry after COVID-19 has also shown that analytics contribute to improved responsiveness and performance primarily through their effects on organizational agility and innovation, highlighting the importance of developing the capabilities derived from

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the development and application of knowledge that allow firms to act on insights quickly and effectively [37]. This requires not only technical capabilities but also interpretive routines, feedback loops, and deliberative processes that enable firms to integrate new analytical insights into existing strategic knowledge and adjust their processes accordingly [22][24]. The actionable guidelines emerging from this synthesis suggest that firms should design decision workflows that embed relevant analytics, establish interpretive environments where knowledge is jointly evaluated, and implement feedback systems that monitor the performance of analytics-informed decisions over time. Together, these mechanisms enable organizations to translate big data knowledge into higher-quality decision-making, characterized by greater accuracy, transparency, and adaptability.

5. Conclusion

This review concludes that effective big data knowledge acquisition operates as a three-stage, resource-dependent process involving data integration, analytical knowledge generation, and organizational absorption and application. Across studies, six critical resources: technological, human, organizational, data, knowledge, and environmental, consistently shape how firms capture, process, and apply data-driven insights. Technologies and tools alone are insufficient, as meaningful knowledge emerges when high-quality data, skilled employees, supportive organizational structures, existing knowledge bases, and environmental conditions work together. These findings clarify how firms can coordinate resources and processes to strengthen their data-driven capabilities, enhance decision-making, and achieve strategic advantages.

Suggestion

To effectively acquire knowledge from Big Data, firms should adopt a resource development strategy that aligns with the technological, human, data, organizational, knowledge, and environmental dimensions. Technologically, firms should invest not only in scalable analytics infrastructure but also in integration architectures and artificial intelligence enabled tools that support real-time processing. Human resources should be strengthened through targeted data literacy initiatives and cross-functional collaboration practices that enable employees to effectively interpret analytical outputs. Data quality, accessibility, and governance are equally important to ensure that analytical outputs are reliable and ethically produced. Organizationally, leadership should institutionalize analytics-informed decision-making routines and create flexible structures for experimentation and rapid adaptation. Knowledge resources should be reinforced through structured learning, knowledge sharing, and the integration of insights into recurring decision workflows. Finally, engaging with environmental resources, such as monitoring regulations, digital ecosystem participation, and leveraging external data partnerships, expands analytical opportunities. Together, these actions form a practical set of guidelines that enable firms to transform raw data into actionable knowledge, sustain organizational learning, and continuously refine their capabilities in dynamic environments.

Future Research

Future research could empirically validate the proposed six-dimensional resource approach across industries using case studies, longitudinal designs, and mixed-method approaches to address the current lack of empirical depth in this literature. Comparative studies across sectors help clarify how resource interactions vary by context and reveal sector-specific pathways for effective knowledge acquisition. Further research should investigate how Big Data capabilities evolve over time and how decision structures mediate the relationship between analytical knowledge and organizational performance. Future research may also explore how industry context and external data ecosystems influence firms' capacity to acquire and apply Big Data knowledge, offering deeper insight into why similar resource configurations produce different outcomes across environments.

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