big data and cognitive computing

Systematic Review

Determining the Factors Influencing Business Analytics Adoption at Organizational Level: A Systematic Literature Review

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Abstract: The adoption of business analytics (BA) has become increasingly important for organizations seeking to gain a competitive edge in today's data-driven business landscape. Hence, understanding the key factors influencing the adoption of BA at the organizational level is decisive for the successful implementation of these technologies. This paper presents a systematic literature review that utilizes the PRISMA technique to investigate the organizational, technological, and environmental factors that affect the adoption of BA. By conducting a thorough examination of pertinent research, this review consolidates the current understanding and pinpoints essential elements that shape the process of adoption. Out of a total of 614 articles published between 2012 and 2022, 29 final articles were carefully chosen. The findings highlight the significance of organizational factors, technological factors, and environmental factors in shaping the adoption of the BA process. By consolidating and analyzing the current body of research, this paper offers valuable insights for organizations aiming to adopt BA successfully and maximize their benefits at the organizational level. The synthesized findings also contribute to the existing literature and provide a foundation for future research in this field.

Keywords: business analytics; big data; systematic literature review; TOE framework; technology adoption

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1. Introduction

In a rapidly evolving business landscape, the capacity to accumulate, manipulate, scrutinize, and draw meaningful conclusions from immense datasets has become an essential competency that organizations must possess to maintain competitiveness [1]. The extensive diffusion of digital technologies and the expanding accessibility of data have engendered a critical dilemma for organizations on how to efficiently manage and leverage this vast pool of data to foster innovation, optimize operational efficiency, and gain an advantageous market position [2].

Business Analytics (BA) is among the technologies used to gain decisive insights from data [3]. Due to its high operational, tactical, and strategic potential, it has attracted the interest of many academics and practitioners across different industries [4,5]. BA is defined as "the process of developing actionable decisions or recommendations based on insights from historical data, as well as frequent monitoring of the performance of business processes through the accurate presentation, multidimensional data analysis, and report creation" [6] (p. 201). The primary goal of BA is to assist organizations in effectively harnessing the value of historical data by utilizing statistical and mathematical models, as well as advanced techniques such as Artificial Intelligence (AI) algorithms [1]. These models and algorithms enable organizations to integrate diverse data sources for optimal decision-making, trend prediction, and other related tasks. Typically, the BA involves a long chain of different analytical techniques to transform data into actions, known as descriptive, predictive, and prescriptive [7]. Each type of analytics has specific purposes, tools, and functions within the overall process.

Descriptive analytics focuses on identifying patterns and trends in data. It involves summarizing and visualizing data to gain insights into past and current business performance. Predictive analytics, on the other hand, employs tools such as machine learning and simulation to develop strategic options. It provides decision-makers with actionable insights, enabling them to forecast future outcomes and anticipate potential opportunities or risks. Meanwhile, prescriptive analytics aims to improve prediction accuracy and prescribe better decision options that generate new value for an organization, such as future expected revenues, profits, intangible assets such as intellectual capital, and opportunities for future growth [8].

The proliferation of Big Data (BD) and the rapid evolution of digital products have prompted many business organizations to explore the potential benefits of BA and consider its adoption [9]. These organizations use BA to develop new strategies, evaluate business strengths and weaknesses, track progress, align business objectives and processes [10], predict market opportunities, identify customer preferences, streamline operations, and mitigate potential risks [3]. As a result, global investments in BA tools are consistently on the rise, and there has been a significant surge in corporate spending on such tools [5,11]. According to a market report (Business Analytics Software Market), the global market for BA solutions was valued at $61.10 billion in 2020 and is projected to reach $177.27 billion by 2030, growing at a compound annual growth rate of 11.2% between 2021 and 2030 [12]. Meanwhile, Alaskar [2] states that a notable increase in the amount of available data is anticipated by 2025, with an estimated volume of 180 zettabytes. The projected surge in data underscores its critical role in shaping the digital landscape of the future, given its potential to be processed efficiently and used effectively in supporting high-risk events and decisions that can significantly impact corporate performance [13].

The abovementioned figures support that BA adoption is essential for businesses, demonstrating its substantial potential. However, notwithstanding the widespread adoption of BA, numerous organizations have been unable to realize the projected strategic advantages [14–16]. Some organizations, for instance, fail to properly plan for BA in terms of acquiring talented personnel with sufficient experience, managing the change related to business processes and organizational decision-making culture, and allocating the necessary financial resources for such investments [15]. In addition, Shi et al. [8] recently drew attention to a concerning statistic revealing that 95% of projects related to analytics-driven innovation encounter failure due to a range of technical and cultural challenges. In the same vein, Conboy et al. [17] indicate that there is still a lack of understanding from a practical standpoint about how to use analytics to improve business, as well as managerial and cultural issues emerge as the primary barriers to the widespread adoption of BA solutions. Moreover, the existing literature on the topic provides inconsistent results and lacks satisfactory evidence on what factors account for the successful implementation of BA, particularly at the organizational level [13]. As such, this highlights the need to investigate the factors that impact an organization's decision to adopt BA effectively to capitalize on its intended benefits.

Therefore, this study adopts a systematic review approach to thoroughly examine various factors that can influence the BA adoption process within organizations, with a focus on technological, organizational, and environmental (TOE) contexts. The TOE framework considers one of the most useful theoretical lenses to evaluate technology/innovation adoption at the organizational level [18]. Therefore, given that the theme of this study is the adoption of BA from the organization's perspective, the TOE framework serves as an overarching theoretical basis for conducting this review, driven by its consistency with other frameworks, such as the diffusion of innovation (DOI) theory [19,20] and resource-based view (RBV) theory [16], as well as the most frequently used technology adoption theory among scholars [21]. In essence, this framework is predicated upon identifying the impact of both internal factors, such as technology and organization, and external environmental factors on the behaviors of organizations towards technology adoption [22]. Thus, this study aims to provide an in-depth analysis of the factors that likely influence BA and related technologies' adoption within TOE contexts in organizations.

Our study holds significant value for researchers and practitioners in IT, big data, and data analytics as it offers a comprehensive overview of the existing literature on the relationship between TOE factors and technology adoption (i.e., BA) within organizations. The research output of this study can aid future researchers in identifying relevant literature on BA adoption to support their research endeavors. The findings of this study can also contribute to a better understanding of the factors that impact BA adoption, thereby aiding the decision-making process of organizations looking to adopt BA effectively.

The remaining part of this study covers an overview of the background information on BA and relevant terms followed by the research methodology, which details the systematic review mapping process and presents research results based on a classification framework. Then, the research discussion of the relevant literature in terms of the technological, organizational, and environmental dimensions of organizational adoption for BA is presented. Finally, the conclusion of the study, as well as limitations and future research directions, are highlighted.

2. Background in Business Analytics (BA)

BA is a term coined by the business industry, which represents an inherently forward-looking concept that evolved from BI [23]. While BI used to focus on descriptive analytics reporting and data integration, BA goes beyond plain analytics and focuses its analyses on prediction and prescription tasks. By using data to create analytical models, BA manages business decisions in the face of an uncertain or unknown future [24]. It is the synthesis and integration of information technology, management science, and statistical analysis to reach the optimum decision for solving business problems that managers face. The primary goal of BA is to improve the way organizations conduct business and drive better business decisions, initiated by the need to either address particular problems or explore and learn from existing data [10]. It enables managers to use data and facts to support their decision-making and improve operations rather than relying solely on experience, intuition, or instinct. Without BA, it may pose challenges for managers in terms of learning from the past or predicting future outcomes [25]. BA facilities how organizations manage their businesses and react properly to market dynamics using various technical solutions [26]. In essence, BA uses IT-based tools such as data warehousing, data mining tools, visualization tools, statistical modelling, and analysis tools, as well as operation research techniques, such as optimization and simulation [27]. Meanwhile, a growing trend has recently been towards incorporating AI into BA [28]. AI technologies such as machine learning and deep learning have revolutionized the field of BA by enabling more predictions on structured datasets for robust data-driven decision-making across all domains [7].

2.1. BA and Big Data (BD)

Eric Schmitt, a former CEO of Google, articulated a famous perspective on data: "Five Exabyte of information were created between the beginning of civilization and 2003, but now that amount of data is generated every two days, and the pace is accelerating" [29]. The advent of digitalization in business and society has contributed to a remarkable surge in data production, widely referred to as BD. This term was initially coined in the 1990s to denote sizeable and intricate datasets emanating from diverse sources and incapable of effectively managing and processing using conventional database applications [30].

BD is characterized by the 5Vs, namely volume, velocity, variety, variability, and veracity [31]. Volume relates to the enormous quantity of daily data generated from various sources such as social media platforms, sensors, and other devices. Velocity refers to the speed with which data are generated, making real-time analysis and processing a significant challenge for many organizations. Variety denotes the broad range of data types available, including unstructured, structured, and semi-structured data. Variability encompasses the dynamic nature of BD, characterized by unpredictable changes in the data's structure, meaning, and quality. Finally, veracity denotes the reliability and accuracy of the data, which can be hampered by various factors such as human error, biases, and inconsistencies.

BD is asserted to enhance organizational agility significantly and possess tremendous value in identifying both opportunities and threats within the context of the Industry 4.0 revolution [32,33]. Organizations nowadays have become more conscious of the significance of analyzing BD to gain insights into their operations and the markets they serve [29]. Within this context, BA has emerged as a crucial technological solution offering sophisticated techniques to analyze BD [11,34]. The momentum of BA and BD is growing at an unprecedented rate due to the arrival of AI [28]. The ability to leverage the value of the increasing amount of large datasets has become an imperative goal in a contemporary business environment, as data are increasingly being recognized as "the new oil" [35]. Having BA capabilities can enable organizations to extract insights from BD, which can help them remain competitive in a rapidly changing business landscape [36].

2.2. BA-Related Terms

The use of the term Business Analytics (BA) is often interchangeable with other similar concepts, such as Data Analytics (DA), Big Data Analytics (BDA), Business Intelligence (BI), and Business Intelligence and Analytics [2,37]. Researchers and practitioners frequently use these terms to refer to the advanced technologies and techniques that are required to handle Big Data (BD). Despite being regarded as an evolution of BI systems, BA and BDA differ due to their development level, offering sophisticated data analysis and reporting techniques [38].

In the literature, there is a lack of consensus on the various terms associated with BD [39]. For example, Yin and Fernandez's [40] systematic review of BA points out that analytics is the abbreviation for BA in business, making BA equivalent to DA in business domains. Additionally, as BA processes large and unstructured data, it can be considered an application of BDA in business. Furthermore, the authors state that BA is the application of Data Science in the business environment. Similarly, Zhang et al. [41] suggest that BA is the application of the technical aspects of BDA, also referred to as Data Science, within business or managerial settings to facilitate informed decision-making. Meanwhile, Duan and Xiong [42] and Sun et al. [43] view BA as the general term for all DA applied to business problems, and Khan et al. [44] and Kristoffersen et al. [45] consider BA and BDA as unified terms in their studies.

On the other hand, Shi [46] suggests that some professional communities use BI and BA to represent BDA. Conversely, Min et al. [15] argue that the concept of BA is broader and more comprehensive than BDA, as it incorporates a vast range of BI tools and AI technologies. However, for the purpose of this study, BI, DA, and BDA are regarded as terms related to BA.

3. Research Methodology

A systematic literature review (SLR) is a process for evaluating, interpreting, and orchestrating the literature that has been produced relevant to the specific research question, a particular topic, or a phenomenon of interest [47]. The main purpose of conducting an SLR is to offer transparent and rigorous evidence that enhances the validity and reliability of research findings while providing directions for future research. The SLR is deemed a more suitable methodology for conducting the present study due to its ability to thoroughly investigate the current literature on the influential factors for adopting BA in organizational contexts. The SLR follows a step-by-step approach that involves defining the scope of the review, establishing research questions and protocols, selecting appropriate evidence, appraising the quality of evidence, extracting and synthesizing data, and reporting and disseminating results [48].

In this research study, the systematic review adhered to the PRISMA guidelines established by Page et al. [49] to ensure transparency and accuracy in reporting the findings. The SLR was conducted in three distinct stages, following the approach proposed by Ali et al. [50]. Figure 1 presents a visual representation of these stages and the associated activities involved in this review.

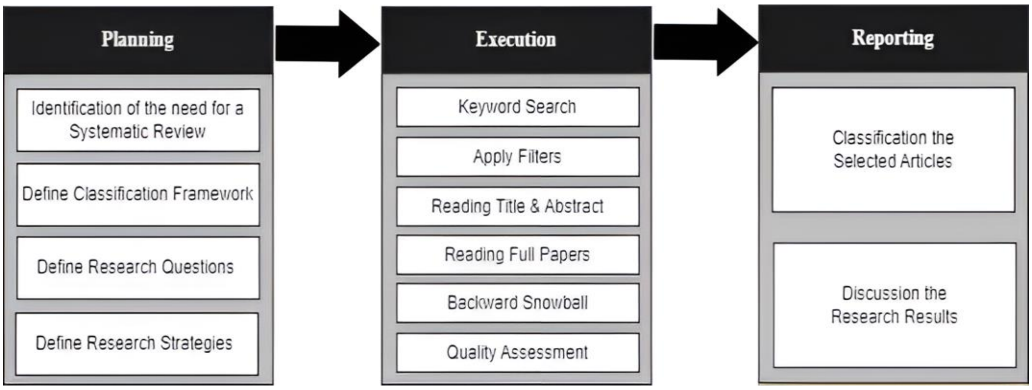

Figure 1. Systematic review stages. Adopted from Ali et al. [50].

3.1. Planning Stage

The initial step in the planning phase involves identifying the needs for a systematic review. The rationale for conducting a systematic review is rooted in researchers' need to comprehensively and impartially summarize all available information on a particular phenomenon. Prior research has demonstrated that various factors are linked to the adoption or usage of BA at the firm level. By adopting the TOE framework, scholars have shown that TOE factors can significantly impact the adoption of BA and related technologies in organizations. Nevertheless, to our knowledge, no systematic review has systematically synthesized these research findings and provided an in-depth analysis of the scholarly aspects of this topic.

The second step in the planning stage involves developing a research review protocol that serves as a blueprint to understand the current factors likely to influence the adoption of BA in the organizational context. In doing so, a review protocol was created based on the classification framework adopted by Sadoughi et al. [51]. The classification framework for this research study consists of three dimensions, namely technological, organizational, and environmental, which group several factors based on the findings of the review of the selected studies. This framework provides a structured approach to analyze the relevant literature in relation to the factors affecting the adoption of BA in organizational settings within the TOE contexts.

The third step in the planning stage is crucial as it involves defining the research questions. According to Paul et al. [52], research questions serve as a guide for the review process, which includes a literature search, study selection, and findings synthesis. Therefore, for this review study, the research question is formulated as follows: *What key factors are adopted in business analytics (BA) adoption at the organizational level?*

The fourth step in the planning stage of this review is to define the strategies for article selection [50]. During this step, the research team established selection criteria for the eligibility review, which are presented in Table 1. The inclusion/exclusion criteria ensured that the literature was relevant to the research question. In addition, this approach ensured that the review results were more accurate, objective, and meaningful while minimizing the risk of bias, thereby maintaining the integrity of the systematic review.

Table 1. Research selection criteria.

Criteria	Inclusion	Exclusion	Rationale
Type of publication	Journal articles [1]	Other types of publications, such as conference papers, books, and dissertations	To ensure that the publications met the standards of academic rigor and had undergone peer review.
Publication year	2012–2022	Publications prior to 2012 and after 2022	To ensure that the literature is relevant and up-to-date for observing trends in the rapidly changing field of technology.
Language	English	Non-English	English is the official language in academic publishing.

[1] To ensure that the included studies were relevant to the research question, we limited our search to empirical journal articles in the BA domain that utilized the TOE framework as their main theoretical framework. This approach allowed us to focus on studies that examined the adoption of BA technologies within organizational contexts.

Moreover, a comprehensive search strategy was utilized, which involved an extensive automated search of the selected database (i.e., Scopus) and a broad manual review of the chosen articles. The automated search yielded a broad array of literature that formed the basis of the study, while the detailed manual review ensured that only relevant articles were considered. During the manual review process, each research article's title and abstract were assessed to determine its potential relevance to the study. Subsequently, a thorough reading of the entire content of the selected articles was carried out to exclude any irrelevant studies. In addition to said strategies, the research team utilized the backward snowball technique to identify any articles that may have been overlooked [53]. This method entailed examining the reference list of the selected articles to identify new and relevant articles for inclusion while eliminating articles that did not meet the research selection criteria from the review.

3.2. Execution Stage

PRISMA is a well-established evidence-based reporting mechanism used in systematic reviews. The data collection process for this review follows the PRISMA flow diagram, which is depicted in Figure 2. The review was conducted between January 2023 and March 2023, adhering to the research protocol set during the planning stage. The primary techniques employed during this phase are described below:

- An initial literature search was conducted using the Scopus database, employing a range of keywords with Boolean operators AND/OR to maximize the number of results obtained. The following keywords were searched within the abstract, title, and keywords of the publications: "Business Analytics" OR "Big Data" OR "Big Data Analytics" OR "Business Intelligence" OR "Business Intelligence and Analytics" OR "Data Analytics", AND "Adoption" OR "Adopt" OR "Usage", AND "Factors" OR "Determinants" OR "Antecedents".
- Following the search, filtering tools were applied to restrict the research results, including source and document type: Journal articles; publication year: From 2012 to 2022, and language: English.
- The resulting articles were then subjected to a manual review process that focused on their titles and abstracts to ensure their relevance to the research question.
- All articles that met the inclusion criteria were fully read to extract relevant information on the topic of this study.
- To complement the automated research strategy, the backward snowball technique was used to identify additional articles that may have been overlooked.
- In order to ensure the inclusion of valuable articles, quality assessment criteria have been applied to assess their eligibility. In doing so, a checklist of questions was prepared, which was adopted from previous studies [50,51]. The checklist covered criteria related to various aspects of the research, including adequate discussion of the research objective, a clear articulation of the research problem/questions, a description of data and adopted methodology, and whether the research results corresponded

to research questions. Articles that met all of these criteria were included in the final review.

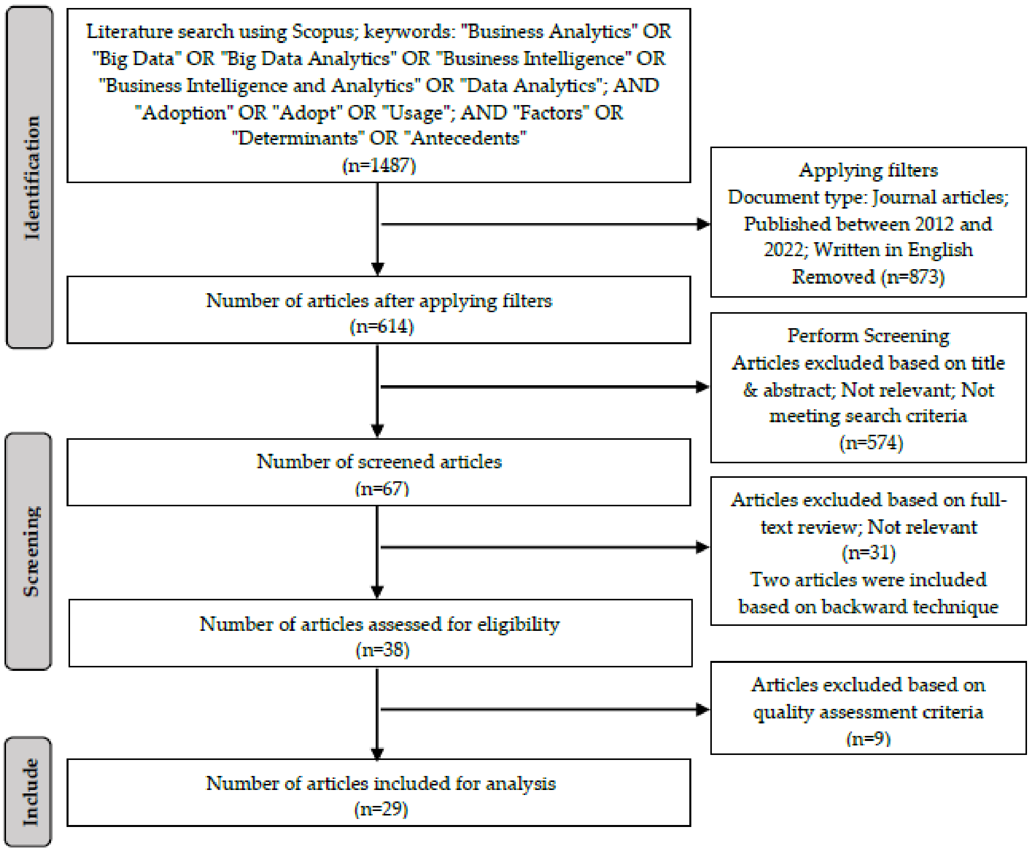

Figure 2. PRISMA flow diagram for systematic review.

3.3. Summarizing Stage

The initial automated search process, utilizing keywords stated in the previous stage, resulted in a total of 1487 articles. Filters were then applied to the retrieved articles, which yielded 614 articles. Following this, the research team performed a manual review by perusing the titles and abstracts to determine the relevance of the retrieved articles, with a specific focus on empirical articles that are closely associated with the topic of the study. This process led to the removal of 547 articles, leaving a set of 67 articles to be considered. The remaining articles were screened further by reviewing the full-text content, which led to 36 articles being classified as relevant to the topic of this study, and 31 were deemed irrelevant and discarded. The backward snowball technique was subsequently applied, resulting in the addition of two more articles. These articles were then subjected to manual review, bringing the total number of remaining articles to 38. Finally, all of these articles were reviewed based on the quality assessment criteria previously described, resulting in the final selection of 29 articles for analysis. The following section presents the results of the analysis.

4. Results

4.1. Some Common Attributes of Selected Articles

4.1.1. Chronological Distribution of Chosen Studies

Figure 3 illustrates the distribution of selected articles considered in this review, spanning the period from 2012 to 2022. Notably, there were no articles published in the years 2012, 2013, or 2014. In 2015 and 2016, one article was published per year. Subsequently, the number of articles gradually increased, with three publications in 2017, four in 2018, and two in 2019. While 2022 witnessed the highest number of articles published, totaling eight. These results signify sustained growth in research interest in BA adoption over the years, with 2022 marking the peak of scholarly activity in this area. Further, this distribution highlights the increasing significance of the adoption of BA and its related technologies, indicating a growing recognition of the potential benefits and implications of BA across various domains.

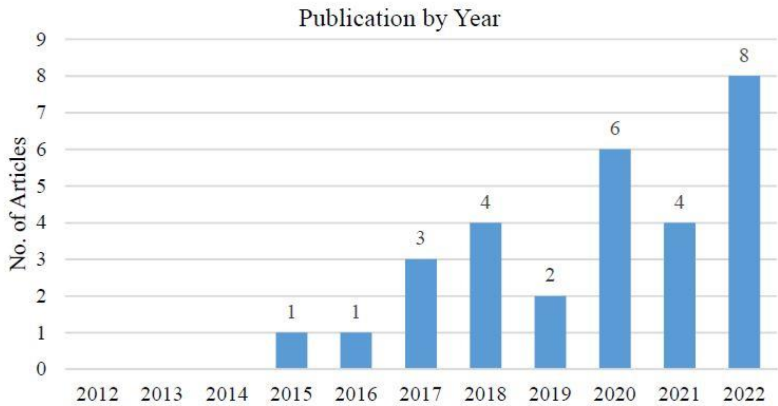

Figure 3. Publications by years from 2012 to 2022.

4.1.2. Distribution of Chosen Studies by Sector

The analysis showed that researchers frequently addressed multiple sectors, which accounted for 48% of all chosen publications. Among the individual sectors, the manufacturing sector had the highest percentage with 17%, followed by the hotel, higher education, and retail sectors, each with 7%. The remaining sectors, which included healthcare, banking, financial services, and insurance, accounted for 3% of the publications each, as shown in Figure 4. These results suggest that research on multiple sectors is a significant area of interest in the BA adoption domain, with a particular focus on the manufacturing sector.

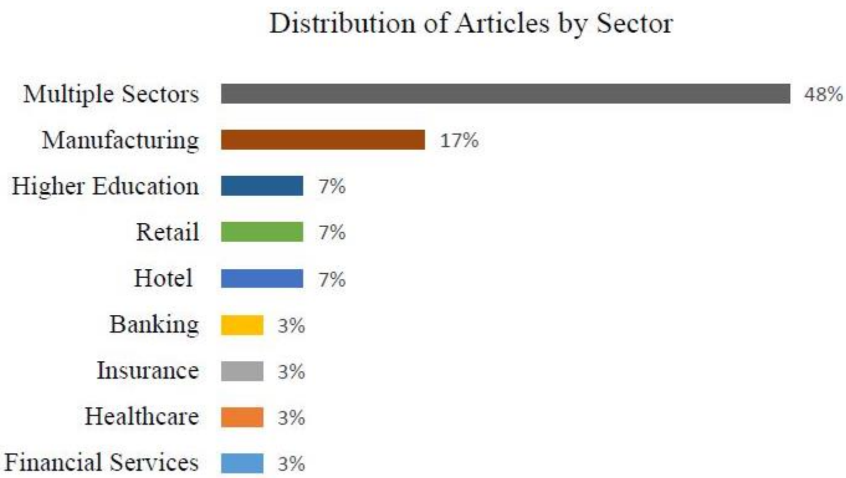

Figure 4. Distribution of articles by sector.

4.1.3. Distribution of Chosen Studies by Geographical Regions

The 29 selected studies for this review spanned at least 16 different countries, as depicted in Figure 5. Jordan has the highest number of articles with five, followed by India with four and Korea with three. In addition, Malaysia, Thailand, China, and Iran each have two articles, while the remaining countries have one article each. In summary, the majority of BA adoption research for this review was carried out in Asia, where it had a significant presence, followed by the Middle East and other regions with fewer articles.

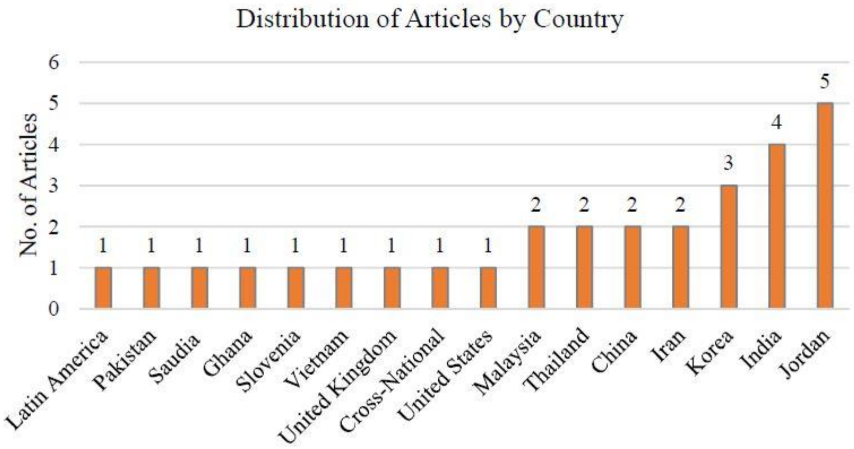

Figure 5. Distribution of articles by country.

4.1.4. Distribution of Chosen Studies by Research Approaches

The analysis revealed that the majority of the selected studies (79%) used a quantitative research approach. In contrast, qualitative research was utilized in fewer studies (14%), while mixed-methods research accounted for 7% of the chosen articles, as presented in Figure 6. These figures indicate that BA adoption research, particularly at the organizational level, is distinguished by a strong emphasis on empirical evidence and statistical analysis to quantify relationships between variables and measure the impact of BA adoption on organizational performance, e.g., [20,54–58].

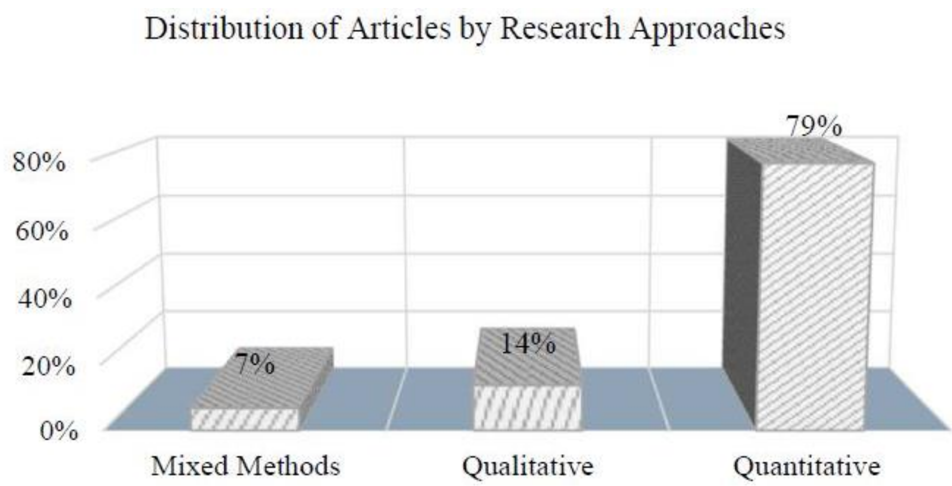

Figure 6. Distribution of articles by research approach.

4.2. Research Classification Framework

The present study conducted a comprehensive review of scholarly articles pertaining to the factors that potentially influence the adoption of Business Analytics (BA) in organizational contexts. In order to facilitate this examination, a classification research framework, as illustrated in Figure 7, was employed. This framework encompassed an analysis of three key dimensions, namely technological, organizational, and environmental factors. These dimensions were derived from the collective findings of the selected studies and served as a basis for grouping various factors. For a more in-depth exploration of the technological, organizational, and environmental factors, please refer to Tables 2–4, respectively. The subsequent section will discuss the findings based on the aforementioned classification framework.

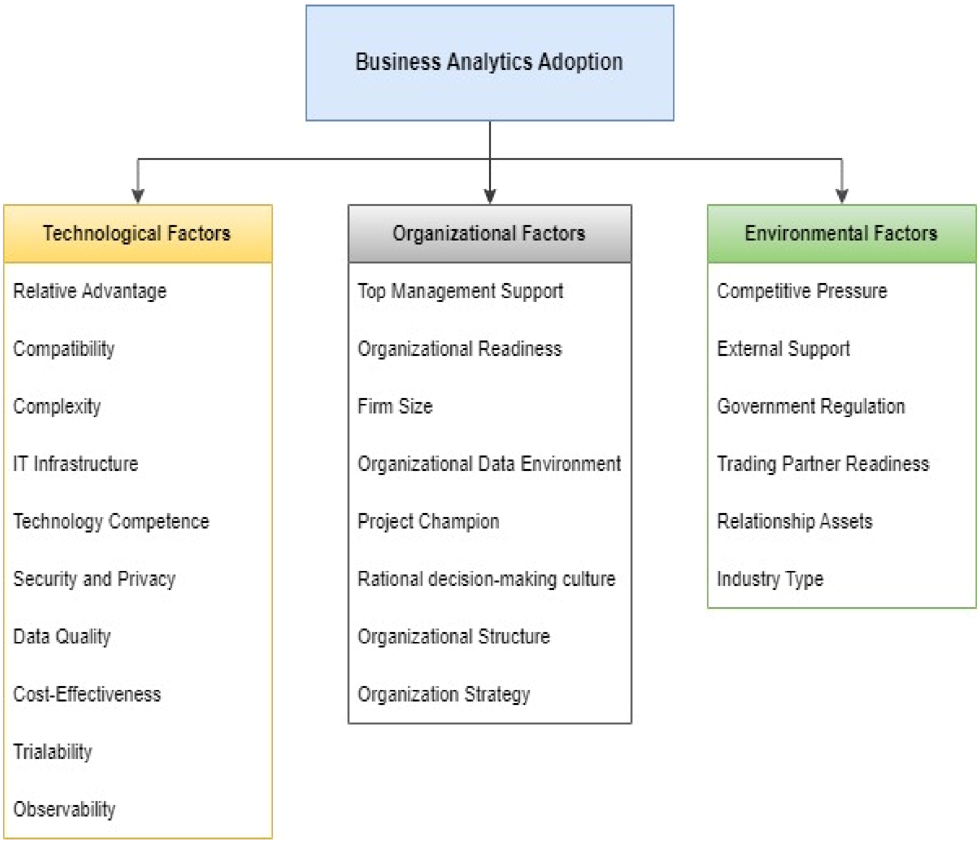

Figure 7. Research classification framework.

Table 2. Technological dimension.

Technological Factors	Brief Description	References
Relative Advantage	The degree to which technology is perceived as superior over other existing technologies utilized in business, alongside the anticipated benefits, including the operational and strategic advantage it confers upon the organization.	[19,21,22,54,56,59–73]
Compatibility	The degree to which a BA is perceived as being consistent and congruent with an organization's existing systems, as well as its alignment with their values, experiences, and needs.	[21,22,25,54–57,59,61–67,69,72–75]
Complexity	The degree of difficulty BA users perceive in terms of understanding and usability.	[21,22,55,56,59,61–67,69–75]
IT Infrastructure	The ensemble of technological components, including hardware, software, networks, and other related components required to support an organization's computational needs.	[13,14,57,58,60,65,68,74–76]
Technology Competence	The ability of members of an organization to adopt, integrate, and use BA in their operations or activities. It entails having the necessary knowledge and skills to leverage technology effectively.	[14,57,58,60,64,67–69,73–75]
Security and Privacy	BA adoption may accompany risks, particularly those aimed at preventing its adoption, such as third parties' tools and assistance. The aforementioned involves measures and controls to protect digital assets and individuals' personal information from unauthorized access, use, theft, or damage.	[21,22,25,61,62,64,72,76]
Data Quality	The degree of accessibility, consistency, and completeness of data needed for conducting analytics.	[13,14,22,25,62,63,70,76]
Cost-Effectiveness	The extent to which the benefits of adopting a BA technology outweigh its associated costs.	[19,71]
Trialability	The extent to which BA technology can be tried prior to adoption.	[21,25]
Observability	The extent to which the results of BA technology are visible to potential adopters.	[21]

Table 3. Organizational dimension.

Organizational Factors	Brief Description	References
Top Management Support	The degree to which upper management understands and values the technological capabilities associated with BA adoption. This process involves fostering a positive atmosphere and allocating sufficient resources to promote its adoption.	[13,14,19,21,22,25,54–62,64–66,68–70,72,74,75]
Organizational Readiness	The willingness of the organization to adopt and effectively utilize BA. It is typically determined by several factors, such as adequate financial resources and an allocated budget for IT, an appropriate level of IT infrastructure, and the availability of skilled personnel capable of effectively implementing and using BA technology.	[19,21,25,54–56,59,61,62,65–67,70,71,73,75,76]
Firm Size	It is typically measured in terms of annual revenue and employee count. Large firms are known to possess a greater capacity for technological investment owing to their annual revenue and the number of skilled personnel who might support BA adoption.	[60,64,67,68,71,72,74]
Organizational Data Environment	The organization's capacity to obtain access to previously inaccessible information and minimize errors during the information retrieval process.	[19,55,69,75]
Project Champion	A management-level individual who actively promotes and supports the adoption and implementation of BA and has in-depth knowledge of the organization's business processes and BA.	[13,19]
Rational decision-making culture	An organizational culture that prioritizes the testing and assessment of quantitative evidence in the decision-making process. Such culture promotes the utilization of data and information to support work processes and perform analyses using state-of-the-art techniques.	[14,19,64]
Organizational Structure	The organizational structure for decision-making. It can be either centralized or decentralized. A centralized organizational structure provides a well-defined hierarchy of authority, whereas a decentralized organizational structure allows for greater creativity and collaboration.	[14,58]
Organization Strategy	A business strategy (i.e., prospector) that emphasizes innovation and growth. It entails organizations taking risks and exploring new markets or technologies by investing in R&D to create new products or services that can lead to new market opportunities. This strategy is appropriate for businesses that operate in highly dynamic environments where technological innovations frequently disrupt the industry.	[58,71]

Table 4. Environmental dimension.

Environmental Factors	Brief Description	References
Competitive Pressure	The extent to which competitors influence an organization's decision to adopt innovative technologies. Early technology adopters typically have a first-mover advantage in a given industry.	[13,14,21,25,55–61,64–75]
External Support	The degree of support provided by vendors or third parties for utilizing and carrying out technology-based solutions, such as consultation, training, or technical support, to assist organizations in overcoming the challenges associated with technology adoption.	[19,21,25,55–58,62,64,72,73]
Government Regulation	Government rules and policies concerning technology adoption may involve incentives, technological standards, or legislation. Such regulations can either encourage or impede its adoption.	[13,14,21,54,58,60,61,65,67,68,70,74,76]
Trading Partner Readiness	Trading partners seeking to adopt technology may have the power and influence to exert pressure on their counterparts. Observing a trading partner's adoption of technological innovation may prompt an organization to adopt the same or similar innovation to demonstrate its ability to maintain a strong business partnership.	[60,68,69,75]
Relationship Assets	The benefits an organization can derive from its pre-existing relationships with customers, consultants, suppliers, partners, and other stakeholders can facilitate the adoption of technological innovations.	[58,75]
Industry Type	The degree to which sector that the organization belongs adopts technology in its operations, activities and provision of services.	[58,75]

5. Discussion

5.1. Organizational Dimension

The adoption of business analytics within an organization requires careful consideration of various organizational factors. These dimensions play a crucial role in determining the success and effectiveness of analytics initiatives. This study identifies a set of organizational factors (see Table 3) related to BA adoption, which are crucial factors that influence the success and effectiveness of analytics initiatives.

Adopting BA involves several key organizational dimensions that play a crucial role in its successful implementation and utilization. One of the critical factors for the successful adoption of BA is the support and commitment of top management [13,21,25,60,62]. Primarily, senior executives endorsing and promoting analytics in decision-making create a data-driven culture [61]. Top management support includes providing necessary resources, allocating budgets, and setting clear strategic goals for BA initiatives. Organizational readiness is recognized as another important factor for BA adoption [54,56]. It refers to the preparedness of the organization to adopt and integrate BA effectively. It involves assessing the organization's technological infrastructure, financial capacity, employee skill sets, and willingness to embrace analytical insights. Assessing and addressing gaps in these areas is crucial to ensure a smooth transition to a data-driven environment. The findings also highlight the vital role of the organizational data environment in adopting BA [55,69]. Specifically, the availability and accessibility of data within the organization significantly impact the adoption of BA. An effective organizational data environment involves data governance, integration, quality management, and security [19]. A well-structured and integrated data environment enables the analytics team to efficiently access, analyze, and derive meaningful insights from data. Furthermore, the project champion is found to be critical for BA adoption [13,19]. A project champion represents an individual or group within the organization who takes the lead in promoting and advocating for the adoption of BA. Project champions act as a driving force, bridging the gap between the analytics team and the rest of the organization. They are responsible for building awareness, gaining buy-in from stakeholders, and ensuring that the analytics projects align with organizational objectives [13].

Importantly, the findings stress that adequate alignment between BA adoption and the overall organizational strategy is deemed an essential success factor [58,71]. An organization's strategic goals, objectives, and priorities should guide the analytics initiatives This alignment ensures that analytics efforts are focused on addressing critical business challenges, improving operational efficiency, and driving innovation in line with the organization's long-term vision. Furthermore, an appropriate organizational structure significantly impacts BA adoption [14,58]. In a decentralized structure, rather than relying solely on a single analytics team for all organizational analysis, the presence of analytical capabilities within individual business functions or departments plays a vital role in facilitating widespread BA adoption. This approach improves domain expertise as individuals can utilize their specialized knowledge to analyze data within their respective areas. By empowering employees at different levels and in various business functions with analytical skills, organizations can achieve higher levels of participation in decision-making, facilitate the circulation of information, provide greater autonomy, and enhance communication flows [14]. At the same time, a centralized structure can significantly support the adoption process by promoting a unified and consistent approach, enabling smoother implementation, and minimizing potential conflicts that may arise from divergent perspectives or competing interests. In addition, rational decision-making culture has a significant role when it comes to BA adoption [14,64]. A culture rooted in rational decision-making actively promotes the utilization of data and analytics as essential components of the decision-making process [14]. It specifically emphasizes the adoption of evidence-based decision making, embraces data-driven analysis insights, and encourages experimentation and continual learning. Finally, the size of an organization can influence BA adoption [64]. Larger organizations may have more extensive data resources and capabilities, enabling them to undertake more complex analytics projects [68,74]. In contrast, smaller organizations may have more agility and flexibility to adopt analytics quickly due to simpler decision-making processes and fewer bureaucratic hurdles. However, regardless of size, all organizations can benefit from leveraging BA to make informed decisions [72].

5.2. Technological Dimension

This study reveals that BA adoption is influenced by various factors within the technological dimension. These factors (see Table 2) play a crucial role in determining the success and effectiveness of implementing analytics solutions within organizations.

Relative advantage is recognized as one of the main motivators to adopt BA [54,62,63]. It refers to the perceived benefits and advantages that adopting BA can bring to an organization compared to existing methods or alternatives. Organizations consider whether analytics solutions can provide better insights, improved decision-making capabilities, enhanced operational efficiency, or competitive advantage. Similarly, the compatibility of business analytics tools with the existing technological environment is another crucial aspect of successful BA adoption [22,55]. In this regard, compatibility refers to the degree to which business analytics solutions can be integrated with an organization's existing systems, processes, and infrastructure. It is essential to ensure smooth implementation and seamless integration of analytics tools into the existing technological environment. Importantly, organizations that intend to adopt BA should bear in mind the effect of business analytics tools' complexity on such adoption [57,65]. The complexity factor relates to the difficulty or simplicity of adopting and utilizing BA within an organization. Complexity can arise from various aspects, such as the technical complexity of the analytics tools, the complexity of data integration and management processes, and the complexity of interpreting and applying analytical insights.

Technology competence is identified as another important factor for BA adoption [64,68]. It refers to the level of technical expertise and knowledge required to implement and operate analytics tools effectively. Organizations need to assess whether they possess the necessary technical skills and competencies internally or if they need to acquire or develop them through training and recruitment. In addition, it is noted that the presence of a robust and scalable IT infrastructure is essential for handling large volumes of data, supporting advanced analytics algorithms, and ensuring the efficient processing and storage of data required for analytics initiatives [68,75,76]. Accordingly, the state of an organization's IT infrastructure significantly impacts BA adoption. Moreover, the findings shed light on the significance of the security and privacy concerns when adopting BA [61,62]. Particularly, security and privacy considerations are crucial when dealing with sensitive business data. Organizations must evaluate the security measures and protocols provided by analytics solutions to safeguard data from unauthorized access, breaches, or misuse. Compliance with relevant data protection regulations is also essential. Data quality is regarded as another critical factor that affects the accuracy and reliability of analytical insights [14,22,76]. Organizations must ensure the availability of high-quality data that are accurate, complete, consistent, and relevant to drive meaningful analytics outcomes. Further, data cleansing, validation, and governance processes play a vital role in maintaining data quality.

The cost-effectiveness factor relates to the financial implications associated with implementing and maintaining business analytics solutions. Organizations need to evaluate the costs of acquiring analytics tools, infrastructure upgrades, training, maintenance, and ongoing support and weigh them against the expected benefits and return on investment. Trialability is also identified as a significant factor for BA adoption [21,25]. It represents the ability of organizations to pilot or test analytics solutions on a smaller scale before full-scale adoption. This factor allows organizations to assess analytics tools' feasibility, performance, and suitability in their specific context, reducing the risk associated with large-scale implementation. Finally, the concept of observability, encompassing the clarity and transparency of the impact and advantages gained from business analytics, plays a crucial role in instilling confidence and garnering support for the continued adoption of analytics [21]. Organizations ought to possess the capability to observe and quantify the results of their analytics initiatives, including enhanced decision-making, improved performance, higher revenue, or cost savings.

5.3. Environment Dimension

The findings of the SLR reveal that BA adoption is influenced by factors within the environmental dimension (see Table 4). These related factors provide a contextual framework for organizations to assess the feasibility and potential impact of adopting BA.

The industry in which an organization operates plays a crucial role in determining the extent of BA adoption [13,59,67,72]. Certain industries (e.g., finance, retail, healthcare) have been recognized as early adopters of analytics due to the abundance of data and the immense potential for extracting valuable insights. Oppositely, industries such as manufacturing and agriculture face unique data challenges that necessitate customized analytics solutions. Additionally, competitive pressure within an industry serves as a compelling driver for organizations to embrace BA. To secure a competitive edge, organizations harness analytics to steer data-driven decision-making, discern market trends, streamline operations, and enhance customer experiences. The imperative to outpace rivals and cater to ever-changing customer expectations consistently propels the adoption of analytics strategies.

The findings suggest that government regulations and compliance requirements have a significant influence on the adoption of BA [14,54,65]. Industries such as finance, and healthcare face severe data privacy and security regulations that pose strict constraints regarding the collection, storage, and analysis of data. To comply with these regulations, organizations must ensure that their analytics practices align with the relevant guidelines. This may involve making additional investments in technology and processes to meet the required standards. The availability of external support, such as vendor expertise and solutions, can significantly impact the adoption of BA [64,73]. Organizations often rely on specialized analytics vendors or consulting firms to provide the necessary tools, technologies, and guidance for successful implementation. The presence of a robust vendor ecosystem and the availability of reliable support can accelerate the adoption process. It is also found that the readiness and willingness of an organization's trading partners to adopt BA can influence its own adoption efforts [75]. Collaborative analytics initiatives and data sharing among partners can lead to enhanced supply chain efficiencies, improved forecasting, and better decision-making. If trading partners are proactive in adopting analytics, it can incentivize an organization to follow suit. Finally, relationship assets have a role to play in BA adoption [58]. Particularly, strong relationships with customers, suppliers, and other stakeholders can be a driving force for BA adoption. Organizations that value their relationships and seek to enhance them through data-driven insights are more likely to invest in analytics capabilities. By leveraging analytics to understand customer preferences, optimize supply chain processes, and personalize offerings, organizations can strengthen their relationships and gain a competitive advantage.

6. Conclusions

This study employed a systematic literature review to explore the organizational, environmental, and technological factors associated with the adoption and implementation of business analytics by organizations. Particularly, this study highlights the multifaceted nature of business analytics adoption, emphasizing the interplay between organizational, environmental, and technological factors. The findings underscore the importance of a holistic approach that considers these factors in tandem when planning and implementing business analytics initiatives. Through an extensive analysis of existing studies, several key findings emerged.

Organizational factors are identified as critical determinants of successful BA adoption. Organizations that foster a culture of data-driven decision-making and have leaders who prioritize analytics initiatives tend to achieve better outcomes.

Additionally, the factors related to the environmental dimension are found to significantly impact BA adoption. Factors such as industry-specific characteristics, competitive dynamics, regulatory requirements, vendor support, trading partner collaboration, and relationship assets played important roles in shaping organizations' analytics strategies.

Finally, the technological dimension-related factors (i.e., data quality and availability, infrastructure capabilities, and compatibility) are identified as crucial enablers for effective BA adoption. These technological factors are found to facilitate the successful adoption and utilization of BA. The insights from this systematic literature review can guide organizations in making informed decisions and developing effective strategies to leverage business analytics for competitive advantage. By understanding the organizational, environmental, and technological factors at play, organizations can enhance their capabilities, improve decision-making processes, and unlock the transformative potential of analytics in today's data-driven business landscape.

Limitations and Future Directions

This research study has some limitations. First, the study focuses solely on the organizational adoption of BA, using the TOE framework as the underlying theoretical lens. Although this approach provides a comprehensive examination of the factors that likely influence the adoption of BA in organizations, it limits the generalizability of findings to other contexts and theoretical perspectives. Other theoretical frameworks or theories could provide additional insights into the organizational adoption of BA, and future studies could consider using multiple theoretical lenses to study this phenomenon. Second, the review is confined to empirical studies published in journal articles. The exclusion of other sources of information, such as conference proceedings and books, may result in the loss of potentially valuable insights and perspectives. Future studies could consider including a broader range of sources to provide a more comprehensive literature review. Finally, the review relies solely on the Scopus database as a source of scholarly literature on BA adoption. While Scopus is widely recognized as a valuable source of scientific literature, it may not capture all relevant studies in the field. Future studies could consider using multiple databases and search engines to ensure that all relevant studies are included in the review.

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