Leveraging AI and ML for Enhanced Business Intelligence Systems: A Research Landscape of Trends, Influences, and Future Directions

Sunil Mandaliya[1], Priti Kulkarni[2]
Symbiosis Centre for Research and Innovation, Symbiosis International (Deemed University), Pune, India [1]
Symbiosis Institute of Computer Studies and Research, Symbiosis International (Deemed University), Pune, India [2]

***Abstract*—This research provides a systematic review of AI and ML applied to the BI context from 2014 to 2024. By characterizing the article and citation distribution and by tracing the topics of publications over time, this study outlines major developments, landmark contributions, and the future outlook of the research discipline at hand. However, despite rapid advancements, existing research remains fragmented. It lacks a consolidated understanding of how AI and ML are shaping modern BI systems, creating an urgent need for an integrated review. Prior studies often examine isolated techniques or industry-specific implementations, but very few provide a comprehensive synthesis that maps long-term trends, methodological patterns, and unresolved challenges in AI/ML-enabled BI. The study reviews more than 200 research articles obtained from top academic databases and finds a rise in the integration of AI/ML with conventional BI systems. Our results show the emergence of real-time, predictive, and automotive analytics as much-needed and valuable to consumers. Artificial Intelligence strengthens the capabilities for visualizing data, so complex information becomes easier to access by those who need it. Research literature shows an increase in publications about AI and ML applications in BI systems because these technologies have gained substantial practical importance. The field of study investigates the ways AI and ML improve BI systems by paying special attention to predictive analytics as well as decision-making processes. The main aspects of interest unite advanced AI implementations with user-centric tools that serve multiple industries. Future directions for researchers are AI ethics in BI, as well as creating simple AI tools for non-programmers and investigating the influence of AI-based BI systems on different industries in the long run. This study also presents future research suggestions.**

Keywords*—*Artificial intelligence; machine learning; business intelligence; digital transformation; data analytics; bibliometric analysis

I. Introduction

Artificial intelligence, along with machine learning, has revolutionized the means by which business intelligence operates in the current business environment. Supposedly simple reporting tools of the past are gradually transforming into complex BI solutions that enable the analysis of existing and future states and make decisions automatically. This evolution marks a revolution in the way many organizations are able to utilize data as an instrument of competitive strategy.

The two technologies, AI and ML, have been adopted by BI systems to provide organizations with deeper insights, automate demanding analytical jobs, and enable them to make better decisions. Nevertheless, the growth rate in technologies highlighted, coupled with the broad presence of the technologies, makes the knowledge area quite dispersed, which needs integration for one to make sense of the current trends and the possible future direction of the technologies.

The digital revolution has become a relentless process, and industries are changing at a historic pace, supported by BI systems and are being further assisted by Artificial Intelligence (AI) and Machine Learning (ML). The use of AI and ML in BI systems makes it easier for organizations to analyze data and mine data, making it faster with more accurate. This study, therefore, employs a bibliometric analysis to understand the trends, impact, and future trajectory of AI and ML in BI systems. To achieve the purpose of the paper, the study draws a wealth of knowledge from global research, influential authors, and primary publications throughout the analysis on how AI and ML are transforming business intelligence.

As the industry continues to shift to digital platforms, more and more companies opt for data-based decision-making to gain a competitive edge and better serve their clients. With organizations today creating large volumes of data from different sources, the ability to handle, understand, and make sense of this data has become a crucial issue. Now, Business Intelligence (BI) systems assist organizations in processing the raw collected data and provide valuable information for strategic decisions are considered critical for industries. However, traditional BI systems are receiving considerable pressure in terms of capability to handle the increased data complexity and volume that are characteristic of today's business environment. Therefore, the incorporation of Artificial Intelligence (AI) and Machine Learning (ML) into BI systems is gradually turning into a revolutionary solution that helps businesses to gather additional insight, make new predictions, and optimize important business decisions that were improbable earlier.

Machine learning and artificial intelligence are two of the greatest inventions of the contemporary data-driven society, which have overlapped many businesses by facilitating automated, advanced work, pattern identification, and enhanced data analysis. These technologies provide robust solutions for firms to augment their BI systems so as to shed light on the nonlinear techniques from descriptive (what happened), to predictive (what will happen), to prescriptive (what should happen).

The study focused on the roles of AI and ML in BI systems with the help of a bibliometric analysis of research trends and influences, and future work. The objectives of this study are to analyze the current state of AI and ML in BI systems, reveal existing trends and patterns, and predict the potential direction of the field's development.

The structure of the study is as follows: Section II covers the necessity of BI systems, AI, and ML to improve these systems, and the existing literature on the subject is discussed. Section III covers the research methodology. Section IV presents a discussion on the results and bibliometric analysis. Section V discusses the research implications with research gaps and opportunities, followed by future directions for research in Section VI. Finally, Section VII concludes the study.

II. Literature Review

A. Historical Evolution of Business Intelligence Systems

BI had its genesis in the middle of the 20th century, with little being formally known as decision support systems (DSS) used by businesses to make sound decisions based on analyzed data. DSS were, in fact, the first kind of BI systems that aimed at delivering historical information and simple analysis to the decision-makers. Nonetheless, with the growing levels of business environment complexity and the vast amount of data gathered over the years, weaknesses of traditional DSS emerged [1].

As a result of the above limitations, BI systems were developed to include enhanced tools for analysis, queries, and report generation for enhanced usability. The implementation of BI technologies had by then become a standard way of business operation in the early 2000s, especially for enterprises [2] to help them determine performance based on past occurrences. However, while these traditional BI systems have provided valuable insight, they remained mostly diagnostic in nature; that is, they told companies what had happened, but they did not tell companies what was likely to happen or even what a company should do.

The introduction of AI and ML systems in recent years has revamped the environment of BI systems. These technologies provide the prospect of performing data mining, pattern recognition, as well as prediction across large amounts of data, with a significantly higher rate of accuracy. With the integration of AI and ML into BI systems, businesses can progress beyond reporting, as well as pursue the future of analytical intelligence and augmented intelligence [3], which empowers a business to predict the future and know what is likely to happen at any given point.

B. The Importance of AI and ML for BI Systems Improvement

AI and ML have revolutionized the ways that businesses tackle the problem of data analysis. Historically, BI systems were mainly historical in their approach and essentially reactive. On the other hand, AI and ML-based BI systems actively contribute where they are programmed to make decisions and suggest recommendations out of actual data and intricate computations. This one alone is perhaps one of the most significant advantages of BI systems using AI and ML, and that is, shifting from a more reactive decision-making approach to a proactive one.

- Automation of Data Analysis: Another benefit of the utilization of AI and ML in BI systems is the possibility of delivering automation of the data analysis. With traditional BI systems, data cleaning, data preparation, and the analytical process involved a lot of manual work. However, the use of AI and ML, a big part of this process, can be done automatically, which saves a lot of time and energy. AI algorithms can effectively work on patterns, trends, and outliers in the dataset to help business organizations make an informed decision-making process effectively and rapidly.
- Predictive Analytics: AI and ML enhance the BI system by introducing the aspect of forecasting with reference to the previous events within a business. This capability is especially ideal in industries including finance, retailing, and healthcare since the accurate prediction of requirements will offer big financial savings and a competitive advantage. For instance, in the retail sector, businesses can apply predictive analytics to predict customer traffic rates, manage inventory, target the right customers, and segment marketing campaigns, while in the healthcare industry, patient prognoses and medical interventions can also be predicted.
- Personalization and Recommendation Systems: Apart from predictive data mining, AI and ML help to create complex recommendation systems to facilitate user-specific client experiences. Such systems have been widely employed in retailing, entertainment, and social networking sites to target bands of products, media, and services, respectively. In terms of BI, recommendation systems help to guide users to useful, informative components or reports about their issues and to recommend certain crucial actions to business leaders.
- Real-time decision-making: One of the most important benefits of using AI and ML in the BI systems is to deliver real-time processing and analytics. Legacy BI systems had major shortcomings in that analysis was executed on a set time interval, which would slow down the actual decision-making process. Real-time analysis of data can be done using AI and ML algorithms, which would mean that businesses can be ready and willing to respond to dynamic conditions. This real-time in fact a key strength of the tool, especially when it comes to Fortune 500 Industries such as finance and logistics, where timing is everything.
- Anomaly Detection and Fraud Prevention: AI and ML are also most efficient in the aspect of searching for anomalous patterns in big data. Fraud detection is especially relevant in industries that require special attention, such as banking and insurance businesses. BI systems based on AI, that work on transactional data, allow identifying fraudulent transactions shortly after their occurrence and notifying businesses about such actions.

- Enhanced Data Visualization: AI and ML also assist in improving data visualization in BI systems because they can generate visualization that focuses on key trends. Historically, BI technology systems, for example, required users to independently build charts and graphs, thus making the processes both slow and error-laden. With the use of AI tools for data visualization, users are able to create a visualization that contains accurate information, and it is insightful to the client for easy issue comprehension by businesspeople.

C. *The Growing Research on AI, ML, and BI Systems*

In recent times, with the developments in the nature and capabilities of AI and ML technologies, there is commensurate interest in investigating the integration of these technologies in BI systems. Various lines of research by both academia and industry are currently being exercised in different areas of this integration, some of which are the basic algorithms for such integration, the influence of AI and ML in decision-making systems, and ethical considerations in the integration of AI in decision-making [4].

The additional thematic shift that is gaining popularity now is the integration of XAI into BI systems. With increasing levels of complexity in AI and ML, there is an increasing demand for the audibility of the decisions. XAI is designed to clarify the work of AI in making decisions and to make it possible to gain the confidence of business executives in BI systems based on artificial intelligence.

Furthermore, the integration of AI and ML with other new technologies like blockchain and IoT enhances the highly effective BI system. These systems can revolutionize industries by offering real-time information from connected products, ensuring information credibility from a blockchain system, and enabling decision-making from an AI/ML system.

D. *Research Objectives*

This study aims to:

1) Discuss the development of AI and ML in BI systems using bibliometric analysis

2) Characterize major areas of concern for research and how they relate to each other

3) Reflect on the roles of prominent books and their authors in defining the field

4) Identify new directions that are possible in a given field.

5) Herein, systematic research gaps will be identified, and directions for further research will be presented.

E. *Significance of the Study*

This research contributes to the existing body of knowledge by:

- Detecting the provenance of works and their further development
- Emphasizing trends in the present and the future opportunities to explore
- As a textual analysis, the findings should be useful to practitioners or individuals interested in the particular topic and for researchers who may employ of similar research methodology.

F. *Theoretical Framework*

The study [5] uses bibliometric analysis and topic modeling to explore the connection between AI and SD research within the business and management landscape. The authors found that while SD and AI are relevant in their respective areas, there are intersections concerning topics such as decision-making, project management, knowledge management, forecasting, supply chain [6], and risk management. The researchers acknowledge some limitations in their methodology. First, using only Web of Science data might not capture the full breadth of research. Second, focusing solely on paper abstracts for bibliometric analysis may omit valuable information contained within the full text, particularly the conclusion sections. To address these limitations, future research could expand the data sources and analyze the conclusion sections of papers, potentially including full-text analysis for a more nuanced understanding [5].

The authors of [7] present a systematic literature review on the application of AI in circular business model innovation. After having removed duplicate items, conference proceedings, and incomplete entries, and by conducting title and abstract screening, the Scopus and Web of Science databases resulted in 145 studies to be examined at this stage. The authors include as many studies as possible at this stage; even technical papers were considered.

The study by [8] discusses issues related to influencing AI-employee collaboration. Methodology of the study comprises a literature review of AI-employee collaboration, identification of knowledge gaps, integrating AI management literature with existing theoretical frameworks, KBV, STS, and OSF, designing an AI-employee collaboration model, and testing the constructed model based on data from UK creative industry managers. The authors in this case have used SEM while analyzing data that would establish causality within the proposed model.

The research [9] is a systematic literature review on the nexus between AI and business model innovation. Aiming to bridge the gap of little research on managing AI-driven business model innovation, through a comprehensive search in four electronic databases, their data collection was in English-language articles published before 2023. The duplicates were removed, and quality filters were placed in terms of ranking journals like VHB, JCR, SJR, among others. After this, the number of articles went down to 649. Narrowing down through selection based on title, abstract scopes resulted in 233 articles. Full-text eligibility assessment resulted in the final inclusion of 167 articles, and 9 more were added with cross-referencing to make a total of 180 articles to be reviewed. The analysis involved summarizing key findings in Microsoft Excel and coding publications using MAXQDA qualitative analysis software. This coding involved open, axial, and selective coding, resulting in 2,413 coded segments and 170 initial codes. The researchers used XMind to compare, analyze, and discuss findings, ultimately identifying 117 first-order terms, 32 second-order themes, and 6 aggregated dimensions. The study acknowledges limitations, including the potential exclusion of relevant non-English literature and potential bias due to the selected keywords and databases. However, the authors argue that focusing on high-quality journals within the management literature strengthens the rigor of their findings.

The study [10] examines artificial intelligence task delegation (AITD). The research design includes a literature review on AITD, formulation of research questions, methodological choices, results analysis, discussion of implications, limitations, mitigation strategies, and a future research agenda.

In [11], the authors examine the historical connection between decision support systems (DSS) and business intelligence and analytics (BI&A). The authors argue that although BI&A is inherently a subfield of DSS, it has become disconnected from foundational DSS research. To demonstrate this, the researchers conducted a systematic review of foundational DSS articles and the corresponding BI&A literature that cited them. They identified 271 DSS articles published from 1970 to 1991 and found that only 29 of these seminal DSS papers were cited in 44 unique BI&A articles. The researchers classified DSS research into four categories: conceptual frameworks, design and implementation, business value and organizational use [12], and cognition and decision making. They then analyzed how BI&A articles utilized and cited the DSS articles within each category. This classification helped identify research gaps in BI&A where the connection to DSS research appears to have been lost. The researchers also collaborated with practitioners to develop a BI&A framework, mapping it to classical DSS components to create a comparative, process-level architecture for converting data into insight. This integrated architecture aims to reconcile the two research streams and highlight the value of revisiting foundational DSS research for contemporary BI&A applications.

The study [13] uses a multiple case study approach to investigate AI-driven digital transformation in five manufacturing SMEs within a shared hub context. While the authors acknowledge that this specific context might limit the generalizability of their findings, they argue that the results are applicable to similar contexts. However, this also means that AI-based digital transformation transcends industries [14]. Future studies can take the direction of focusing on industries other than manufacturing-for instance, B2C-and explore the orchestration of AI resources in AI implementation through such industries.

The study [15] is a systematic literature review (SLR) report on the applications of AI in improving SCRes. Prior reviews just made mentions of abstract concepts regarding AI and SCRes without elaborating on how AI techniques improved SCRes, hence coming to fill the gap in this study. The study bridged that gap with the use of the PRISMA methodology. An automatic search with keywords in AI and SCRes in Scopus yielded 824 articles, which after deduplication, gave 799 articles. Their language, date of publication within the scope of 2010 and 2022, and peer-reviewed narrowed them down to 425 articles. Abstracts and conclusions were read to gauge the relevance of articles to AI techniques and SCRes antecedents and 302 articles remained. All relevant articles were read in full-text and additional records in Google Scholar, together with their citation references, revealed the final sample of 106 articles to be analyzed to understand how AI techniques could potentially be applied to enhance SCRes. This included those AI techniques used, their inherent capacities, and how these had changed the antecedents and phases of SCRes.

The most occurring keywords had been discovered to include supply chain, resilience, risk management, and machine learning. Such keywords indicate research focus on handling the disruptions in a supply chain through resilience and risk management but with AI, especially machine learning, as emerging tools. On the same note, the researchers demarcate the dominating incidence of some journals and authors in the AI-SCRes field.

The systematic review [16] focuses on AI algorithms and decision support tools for predicting and preventing pressure injuries (PIs). The authors conclude that, up to date, there have been very few reviews that merged AI and DSS in the prediction or prevention of PI. The authors narrow down the scope using the PRISMA-DTA guidelines by English language publication that utilizes AI and ML algorithms or DSS for PI prediction and prevention. In the search, 107 papers were found; however, 82 were excluded because of a lack of focus on AI or DSS for the prediction and detection of at-risk patients or in giving PI prevention suggestions. The paper was made in computer vision applications and excluded those that do not use EHR to predict HAPIs.

The paper [17] performs a scientometrics analysis on the performance, collaboration dynamics, and impact of scholarly publications on AI applications. Reviewing 3767 reviews cited 63,577 times, the paper signifies significant scholarly engagement within AI research. They used indices that quantify collaboration; these involve the number of contributing authors, (NCA), average authors per co-authored paper AACA, collaboration index, CI, and collaboration coefficient, CC. Several such indexes were also utilized to scrutinize citation, among which were the h-index, g-index, and i-index to calculate the review articles.

In this regard, the paper [18] conducted a bibliometric analysis of the literature published between 1990 and 2021. The paper discussed using AI in innovating B2B marketing. The present study had set out to address some of the challenges scholars pose while trying to keep up with the tremendous growth in research in the area. Conceding the fact that the current approaches to systematic reviews such as the structured literature review and meta-analysis impose constraints in the management of large volumes of research, the authors assert the suitability of bibliometric analysis. What is used for it is the method in order to find out the significant research areas, authors and journals, and the further research opportunities.

From the five domains discussed in the study, the research outlines trends and possible future development of AI in B2B marketing innovation in each of the domains. Through a meta-analysis of citation data, as well as content analysis, the researchers provide an extensive discussion of the state of the field and potential directions for future research.

The study done by [19] give a comprehensive review of AI in marketing environment. The reviews and meta-analyses, the authors argue for the effectiveness of bibliometric analysis in handling the vast quantity of research. They use this method to identify prominent research domains, influential authors and journals, and future research directions.

Recognizing the importance of AI in future developments of technologies, this work [20] examines the impact of AI on business and economics publications with the use of a bibliometric approach. The two databases chosen by the researchers are Web of Science (WoS) and Scopus databases, as these are two of the most reliable and full-coverage sources of the peer-reviewed research literature. They use VOSviewer software to construct the diagrams of co-citation and keywords, with respect to the direct citation relation that is used to define the relatedness of the publications fast.

The study [21] aims to review the role of AI together with the existence and relevance of big data in decision-making. In their work, the authors focus on the lack of literature with a focus on the definition of the new generation of technologies as applications of AI. They map the trend of publications on AI in the Big Data context and note increased attention to this topic since 2011.

A systematic literature review (SLR) [22] aims to perform to analyze the findings of prior studies revolving around AI and innovation. The researchers opted to use SLR because it is able to provide objective findings and conclusions. For this purpose, they entered the keywords including AI and innovation in both Scopus and WOS databases and used filters like Documentary language, Document type – Article and Review paper only, subject area – Business, Management and Accounting, Decision Science, Economics, Econometrics and Finance. They were able to screen out 266 duplicates, and their final sample size amounted to 1448 articles. The researchers screened and sorted the data to determine the most frequent authors and publications, current and emerging themes, theoretical frameworks, and research methods employed in the field. They also identified the patterns of research activity to establish gaps in knowledge by conducting a bibliometric study.

The study [23] aims at investigating the process by which BDA connects with performance by employing bibliometrics. To this end, the authors endeavored to explicate the historical development and current state of affairs in this domain and highlight research prospects.

To avoid a systematic bias in the review, the authors emailed potential 47 BDA and performance experts based on their suggested keywords and ISI Web of Knowledge database. They then used minimum citation rate, and got 1252 second-generation papers for inclusion in the analysis. The researchers then conducted three bibliometric analyses: Document co-citation analysis, algorithmic historiography, and bibliographic coupling formed important components. The study found 10 research themes within the BDA-performance field, starting with a large, fundamental BDA cluster, moving up to more specific areas such as customer analytics and corporate social responsibility research. Studying the literature, the two major evolutionary developments were identified that employ statistical and algorithmic approaches to finance and customer-orientation streams within BDA research.

In fact, the present paper [24] is devoted to the analysis of DI&A, BD, AI, HAI in the context of the public sector considering the effectiveness of decision-making. The authors review 161 papers in English published between 2007 and 2021 in Web of Science (WoS), Scopus, and Google Scholar (GS) databases using VOSviewer. The authors intend to present an introduction to the field, reviewing subjects of interest, citation practices, publication pathways, and collaboration maps and finally, pointing to possible research agendas.

The research of this paper [25] aims at identifying the trends of big data and predictive analytics in BI using bibliometric analysis with CiteSpace on 681 non-duplicate research papers collected from WoSCC and Scopus. More specifically, the authors select contributing countries/institutions, authors/journals, research mapping trends, cross-disciplinary, and the evolution of new hotspots. The study will endeavor to offer a broad perspective of the area and should consequently be beneficial to guide future research endeavors into big data and AI-driven BI applications [26].

The author [27] focuses on examining the AI and blockchain synergized business applications techniques based on bibliometric content analysis. To achieve that, the analysis of 106 articles identified in Scopus is conducted to reveal the general publication trends, the most popular and impactful works, the main research topics and directions, and the potential application fields. The researchers start by pointing out that despite the growing trend of applying AI and blockchain technologies in business, there is a dearth of impartial post-mortems of the combination of both technologies. They then use VOSviewer and Gephi for data analysis, where they make a network or word cloud to display information in the form of a network view for representing relations or a word cloud view for representing important keywords, respectively.

The study [6] examines the role of AI and ML in SCM using bibliometric and network analysis of 338 highly cited papers indexed in the Scopus database between 2002 and August 2022. In other words, the research objective of the study is to discover innovative opportunities and comparatively unknown areas for AI and ML application in the process of supply chain digitalization.

Systematic review of AI in cellular networks [28] shows that machine-learning agents deployed across design, operation and optimization consistently improve core KPIs - blocked-call and hand-off rates, signal quality, latency and throughput - yet most studies still optimize each metric in isolation and struggle with cost-effectiveness.

The authors claim research demands a more profound evaluation of AI and ML effects in SCM, considering that previous reviews have addressed these subjects separately or involved only a limited number of articles. The researchers apply analytical and computational methods to find out publication trends, authors, prominent journals, and topics. Their study comprises of qualitative data analysis, an analysis of the literature by computing the bibliometric analysis, and network representation for the comprehension of concepts like AI and ML regarding SCM.

Enterprise Management Systems (EMS) is considered a vital business function for ensuring business continuity; it should exploit the power of AI and analytics to assess risks more significantly. In the paper [29], the design of an Improved Metaheuristics with Deep Learning Enabled Risk Assessment Model, IMDLRA-SES, that comprises business risk selection and deep learning-based prediction has been aimed at producing superior accuracy on credit datasets up to 95.70% and 96.09% levels against traditional financial risk identification methods with robust firm stability for longer periods.

The conjunction of AI, big data, and IoT in the amalgamation of Society 5.0 has triggered and changed the face of 'the new' personalized customer engagements related to Marketing 5.0. The paper [30] delves into a literature review to discuss predictive modeling in the context of sentiment analysis in Marketing 5.0, thus providing for a case of a model that can be based upon sentiments to improve the process of the buyer's journey. It draws attention to the importance of predictive and sentiment analysis to emphasize their critical roles in fine-tuning customer experience and improving marketing efficiency [31]. The review identifies gaps in existing research, documents the evolution of marketing, and analyzes AI's transformative role using the Prisma-P methodology.

For inventory management, this study proposes a machine learning-driven model, especially for demand-based stock control, particularly for perishable and deteriorating products in uncertain settings. The model [32] accounts for fuzzy variables like degradation rates, optimizing ordering cycles and inventory levels while holding costs at minimum, reducing both costs of carbon usage and emissions. Seasonal demand forecasting improves predictions associated with deteriorating items further; comparative analysis shows how AI-enhanced forecasting provides a better forecast than fixed demand models. Sensitivity analysis guides managers on when to adjust the inventory.

Advanced digital technologies, AI, machine learning, and blockchain in logistics are revolutionizing multimodal transportation systems with objectives of greater efficiency and sustainability. The technologies identified in the review [33] are critical enablers for smarter logistics, new business models, and environment-friendly solutions. Yet, these technologies impose policy and practical implementation challenges; their promotion improves the sector's overall sustainability in its environmental, economic, and social dimensions.

Besides this, AI and machine learning-based business intelligence systems enable the integration of data and assist organizations in trend identification and decision-making. Using a machine learning-based framework to analyze the network management for BI, the research [34] analyzes BI through a multiagent Markov probabilistic reinforcement model. By analyzing such parameters as accuracy and packet delivery, the research works toward optimizing business processes by leveraging AI-driven solutions for firms to make the appropriate technology choice for automated process management. Table I summarizes the key studies reviewed and highlights the specific advantages and research gaps identified across prior work.

TABLE I. GAP ANALYSIS

Study	Advantages	Gaps
Armenia et al. (2024)	Bibliometric analysis and topic modeling uncover intersections between AI and SD in business topics like decision-making and knowledge management.	Expansion of sources and inclusion of conclusions/full-text analysis suggested for deeper insights.
Madanaguli et al. (2024)	Comprehensive SLR on AI in circular business models, using Scopus and WoS databases with careful screening of duplicates and incomplete entries.	Limited focus on abstracts and titles may omit depth; inclusion criteria could miss recent or highly specialized works.
Chowdhury et al. (2022)	AI-employee collaboration model designed and tested in UK creative industry; methodological rigor with SEM for causality.	Focused on the UK creative industry, limiting broader applicability. Further studies could examine diverse industries.
Jorzik et al. (2024)	Systematic literature review with high-quality journal filtering and robust coding for AI-driven business model innovation.	Non-English articles excluded, risking language bias. Expansion beyond English sources is suggested.
Recupito et al. (2024)	Research design includes a systematic review of AI task delegation with future agenda.	Limited by focus on literature review only. Empirical validation of proposed insights could enhance applicability.
Phillips-Wren et al. (2021)	Systematic review connecting DSS and BI&A; provides a framework reconciling the two fields.	Analysis of limited citation connections between DSS and BI&A; a broader dataset could strengthen the findings.
Peretz-Andersson et al. (2024)	Case study approach on AI in SME manufacturing for digital transformation; context-specific findings with possible similar applications.	Limited generalizability beyond manufacturing SMEs. Calls for studies in B2C and other sectors.
Kassa et al. (2023)	PRISMA-based SLR on AI in SCRes, identifying AI's role in enhancing SC resilience.	Limited to abstracts and conclusions in selection; additional full-text analysis could add depth.
Toffaha et al. (2023)	Systematic review of AI-DSS tools for predicting and preventing pressure injuries, narrowed with PRISMA-DTA.	Narrow focus on EHR data and specific algorithms may limit generalizability to non-EHR settings.
Raman et al. (2024)	Scientometric analysis of AI research, measuring collaboration with indices like h-index and g-index.	Limited analysis on the context of collaboration, lacking qualitative insights on collaboration dynamics.
Han et al. (2021)	Bibliometric analysis of AI in B2B marketing identifies trends and research opportunities.	Constrained by limitations in SLR/meta-analysis for managing large research volumes; broader approach could address data complexity.
Ruiz-Real et al. (2021)	Uses VOSviewer for bibliometric analysis on AI's impact in business/economics; strong visualization of co-citation and keyword trends.	Limited to two databases (WoS and Scopus), potentially omitting broader literature.
Haleem et al. (2022)	Systematic review on AI in marketing; uses bibliometric	Limited by scope in foundational areas of AI marketing; further

Study	Advantages	Gaps
	analysis to identify key domains and future research.	studies could delve into niche areas.
Duan et al. (2019)	Focuses on the roles of AI and big data in decision-making, providing historical context and research mapping.	Over-reliance on certain databases might miss emerging, non-mainstream studies.
Dwivedi et al. (2023)	SLR on AI and innovation with extensive keyword screening and rigorous sampling.	Excludes non-English articles and industry-based insights; future studies could consider these aspects for more generalizable findings.
Batisti and van der Laken (2019)	Bibliometric analysis on BDA and performance, identifying 10 thematic clusters.	Exclusion of expert insights might limit a comprehensive understanding of practical implications.
Di Vaio et al. (2022)	Analyzes AI and big data in public sector decision-making with bibliometric tools like VOSviewer.	Excludes newer and potentially relevant non-peer-reviewed sources; industry focus may add practical value.
Chen et al. (2022)	Identifies trends in big data and predictive analytics in BI with CiteSpace for cross-disciplinary analysis.	Limited by database constraints; could be expanded to cover emerging research not indexed in WoSCC and Scopus.
Kumar et al. (2023)	Examines AI and blockchain in business applications with VOSviewer and Gephi for data visualization.	Limited to Scopus database; expansion to other databases could enhance robustness.
Rana and Daultani (2023)	Uses network analysis on AI in SCM, identifying research gaps in AI's role in supply chain.	Limited to Scopus database; broader inclusion criteria could cover more diverse studies.
Katib et al. (2024)	Introduces a deep learning-enabled model for risk assessment in enterprise management systems.	Limited validation on credit datasets; testing on diverse datasets could prove robustness.
Gooljar et al. (2024)	Literature review on predictive modeling for sentiment analysis in Marketing 5.0; identifies gaps in customer engagement.	Limited empirical evidence; further empirical studies could substantiate claims.
Namwad et al. (2024)	Proposes a machine learning-driven inventory model for deteriorating items, addressing demand forecasting.	Limited to specific product types; wider application for various industries suggested.
Fareed et al. (2024)	Systematic review of AI, machine learning, and blockchain in logistics; identifies sustainability challenges.	Limited focus on practical implementation barriers; case studies could address industry-specific issues.
Wu and Qin (2024)	Analyzes BI through a multi-agent probabilistic reinforcement model, optimizing network management for BI.	Limited focus on a single framework; future research could consider multiple AI frameworks for BI management.

III. Research Methodology

A. Data Collection

This research aimed at including only the recent developments, which is why only articles published between 2014 and 2024 within the scope of peer-reviewed journals were considered. Four primary academic databases were consulted for a comprehensive literature review: Web of Science, Scopus, IEEE Xplore and ACM Digital Library. These databases are indeed popular sources in the field of technology and data science and mostly contain research papers of good quality which are peer-reviewed. Through these databases the study was able to ensure that the literature reviewed was not only valid but also current in its subject of discussion which is focused on AI ML applications in Business Intelligence (BI) systems.

Various article search terms were employed for this study, wherein the main keywords are Artificial Intelligence (AI) and Machine Learning (ML) in conjunction with Business Intelligence. In this particular research, the author conducted the following search: "Artificial Intelligence" AND "Business Intelligence," "Machine Learning" AND "Business Intelligence", "AI" AND "BI Systems", "Predictive Analytics" AND "Business Intelligence". These kinds of search terms helped in carrying specific search as it guaranteed that only the studies on integrating AI and ML in BI systems were retrieved. This systematic approach allowed the research to capture a set of literature that maps out the historical development, trends, and future development of AI and ML for improving BI, and their impact on predictive analytics and decision-making in organizations.

B. Data Analysis

Advanced tools were adopted for the mapping of research landscape related to AI and ML in BI: for instance, the bibliometric analysis adopts a couple of advanced tools that enable it to make visualizations for the network of the authors, institutions, and certain key themes to enable bibliometrix (R package) in facilitating the analysis of proper statistical measures towards metrics and trends of citation and other indicators of the publication. It facilitates looking into the productivity and researching trends by indicating the research impact in terms of trends. This could allow CiteSpace to map emerging topics and shifts through the years, which would emphasize research bursts and pivotal developments in AI and BI across the last decade. Both resulted in a complete outline of where the field has evolved and with what influences.

C. Analysis Parameters

The following parameters were analyzed:

- Publication trends
- Citation patterns
- Author collaborations
- Keyword co-occurrence
- Thematic evolution
- Geographical distribution

IV. Results and Analysis

A. Publication Trends

The analysis reveals a significant increase in publications related to AI and ML in BI systems over the past decade. The number of publications has grown exponentially, with a particularly sharp increase observed from 2019 onwards.

The yearly trend for research publications related to "AI and ML for Enhanced Business Intelligence Systems" between 2015 and 2024 is presented in the chart. There has been a gradual increase starting from around 2015; interest in the topic has gradually built up. The number continued to rise upward; by 2019, there was a marked spike when the publication surpassed 500 in 2023. The publication count decreases in 2019 and grows steadily again in 2020, indicating renewed and increasing attention paid to the application of AI and ML in business intelligence. From 2020 through to 2024, growth trends continue, showing the extension of commitment to research related to the application of AI and ML in business intelligence. Presumably, this is a direct result of the evolution and importance of these technologies and their role in strategic business decisions. From 2024 is expected to follow upwards, and it is believed that interest and output research in this field will increase. This trend (see Fig. 1), therefore, demonstrates the significance of AI and ML in the developing environment of business intelligence and predictive analytics.

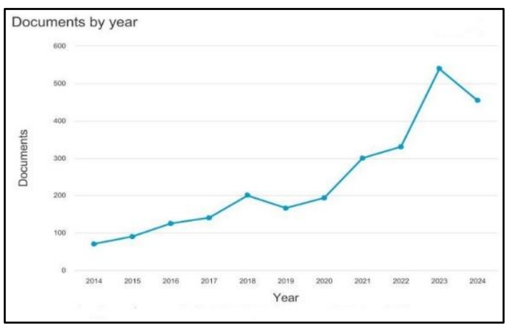

Fig. 1. Publication trend.

B. Inclusion and Exclusion Criteria

To ensure the scientific quality and relevance of the review, clear inclusion and exclusion criteria were applied. The workflow of the study is represented in Fig. 2.

Inclusion criteria were:

1) Peer-reviewed journal articles published between 2014 and 2024.

2) Articles written in English.

3) Studies explicitly examining the use of AI and/or ML within Business Intelligence, decision support, or data-driven analytics.

4) Articles providing sufficient methodological detail to support bibliometric or thematic analysis.

Exclusion criteria were:

1) Conference abstracts, Thesis, books, editorials, and non–peer-reviewed material.

2) Studies focused purely on algorithm development without BI relevance.

3) Articles lacking adequate methodological information.

4) Duplicate records across databases.

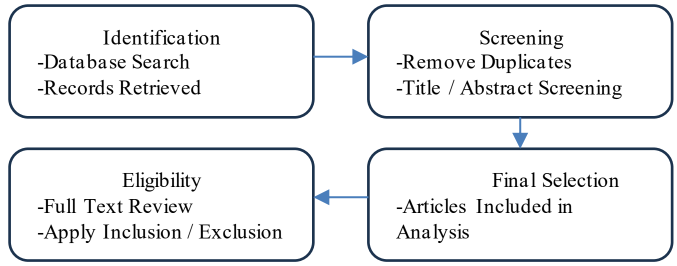

Fig. 2. High-level workflow of the study selection and review process.

C. Citation Analysis

This is a co-authorship network visualization, generated using VOSviewer. This tool is widely applied to map and visualize bibliometric networks.

Node Representation: In a node, an author is represented. Larger nodes mean more publications or citations from authors, depending on what you have selected while running VOSviewer.

Color Code: A color reflects the number of authors who co-authored under this color group and had a high probability of collaborations in the given color. For example, in red, there are more co-authorings of Andreja Pucihar and Doroteja Vidmar between themselves, but less frequently with the rest of the authors under all other colors. Edges, or Links: Lines describe co-authorships; bold lines illustrate more and denser co-authorships within the interlinked authors.

Clusters: The network has been divided into some clusters, each normally formed by a group of collaborating authors who are working within their cluster more intensively than with other members in this network.

Co-Authorship Network Interpreted: This co-authorship network indicates authors who closely collaborate, probably due to similar research interests, physical location, or institutional ties. This may be useful in determining influential authors and the structure of collaboration within this community of scholars.

This visualization, here in Fig. 3, gives insight into the collaborative patterns among the authors, which helps explain the relationships and potential influence of the field represented by this work.

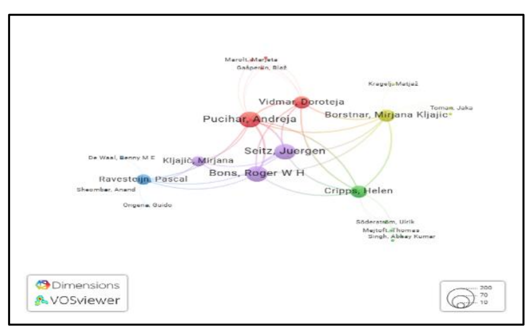

Fig. 3. Citation Analysis.

D. Thematic Analysis

Fig. 4 also shows the distribution of the documents by subject area, revealing the broad areas of interdisciplinary research interest. Computer Science is the most popular specialized area, which comprises 34.7% of the overall announcements; thus, the sectors, including software development, machine learning, and artificial intelligence, are highly developed. Engineering subsequently at 18.6% – meaning applied sciences and technology, and often overlapping with Computer Science in areas of interest as systems and robotics. Computer Science, Information Systems and Technologies, and Engineering each take 9.5% followed by Mathematics at 8.5% and Decision Sciences at 8.3% which are critical in processes that support data science, algorithms, and analytics that form the basis of most technologies. Business and Management (6.2%) is also significant, as there seems to be concern with the ramifications of technological development on organizations and the economy, including issues like managerial innovation and strategic management of technology. Social Sciences (3.8%) offers comprehension of social effects that the technology has, interactions between humans and the technology, and some ethical issues regarding technology advancement.

In terms of the fields of study, the Physics field (2.8%), Medicine (2.6%), and Economics (2.5%) show that the research has scope in physical sciences, healthcare, and technology offerings in medical informatics, as well as in modeling the economy. Energy emerges at 3.3% indicating a focus on sustainability and energy technology, and recommending further research into sources of energy for efficiency, as well as new methods of harnessing energy. Last, there is an "Other" group, which ranges from 8.8%. It can contain such topics, which are not discussed often or are interdisciplinary, so once again, the variety of the topics reflects the density of the research. On the whole, specialization indicates dominance of Technology and its Utilization from different fields, with a proper mix of Science, Business, and Social Sciences making this research collection a Technological special ops influencing Science, Business, and the World.

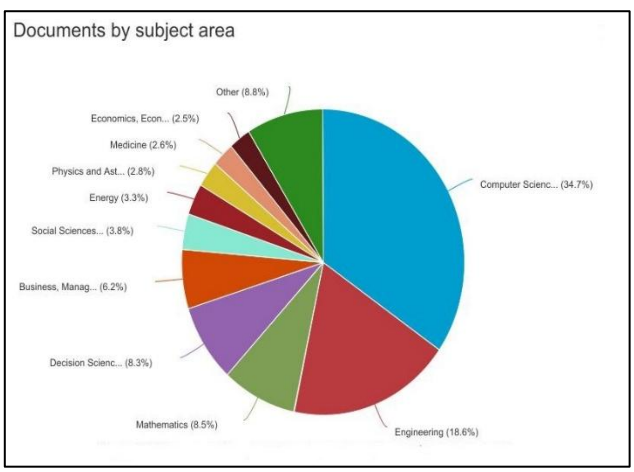

Fig. 4. Major research themes.

E. Geographical Distribution

Fig. 5 illustrates the number of research papers produced by various countries or territories. This is a horizontal bar graph displaying the document counts sorted by nation. The data highlights the comparisons of document totals across multiple countries. India stands out with a considerable lead, presenting around 700 to 750 documents, while the United States follows with about 400 documents. China holds the third position with approximately 200 documents. In the middle tier, authors find the United Kingdom, Germany, and Italy, each contributing around 100 to 150 documents. The lower tier is made up of Australia, Saudi Arabia, Spain, and Malaysia, with each registering fewer than 100 documents. The chart is structured in descending order from top to bottom, allowing for quick recognition of which countries have the highest and lowest numbers of documents. Each nation is depicted with a blue bar that stretches from the y-axis, while the number of documents is displayed along the x-axis, which ranges from 0 to 800. The research reveals significant geographical clusters of research activity.

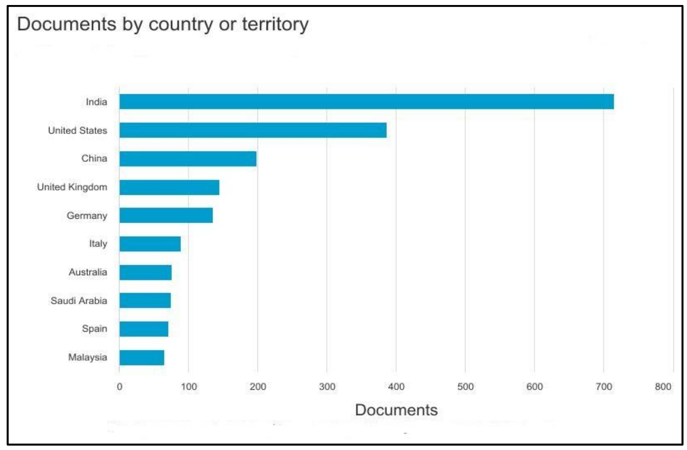

Fig. 5. Documents by country or territory.

V. Discussion

A. Key Findings

AI with ML has dramatically increased its integration within BI systems, which has led to traditional BI tools developing into more complex solutions. These solutions are able to analyze existing and forecasting data while automating decision processes [35]. Organizations can now leverage data as their competitive asset because of this advancement. Driven by AI and ML technology adaptation within BI systems, organizations gain enhanced analytical benefits that transform their decision-making processes. These technologies expanded rapidly, resulting in fragmented knowledge that needs unified handling. The conventional BI structure remains under pressure because of growing data intricacy and volume. New business decisions, as well as enhanced predictions and insights [36], can be achieved through the incorporation of AI and ML solutions. AI, together with ML in BI systems, offers businesses the opportunity to extract value from data beyond descriptions by creating analytic methods that predict and prescribe business actions [37].

Through AI and ML applications in BI systems, organizations achieve automated data analysis together with predictive processes and personalized recommendations, and real-time decisions while identifying anomalies and preventing fraud and improving visual analytics [38]. The scientific research about uniting AI and ML capabilities with BI systems shows increasing interest through studies on fundamental algorithms in combination with AI and ML [39], effects on decisions and ethical practices. XAI systems have become more prevalent because they make AI decision-making operations more understandable. Researchers are investigating how AI and ML cooperate with blockchain and IoT to advance BI systems even more.

The number of publications dedicating research to AI and ML's application in BI systems has experienced a substantial rise in the last decade, followed by a rapid escalation between 2019 and now. The research spans multiple disciplines, with Computer Science (34.7%) dominating, followed by Engineering (18.6%), and Information Systems (9.5%), showing the cross-functional nature of AI/ML in BI. Computer Science is the most popular subject area, followed by Engineering, indicating a strong focus on technology and its applications. Other fields, such as Business, Management, Social Sciences, and Mathematics, also play a significant role. India leads in the number of research documents, followed by the United States and China. Research has evolved from basic BI system enhancement to more sophisticated applications, including real-time analytics, predictive modeling, and automated decision-making. Studies consistently highlight the complexity of integrating AI/ML with existing BI systems, particularly in terms of data quality, system compatibility, and user adoption.

B. *Research Gaps*

Despite these advancements, several research gaps exist.

- There is a need for integration of the dispersed knowledge areas of AI and ML in BI.
- Traditional BI systems are limited in their capacity to handle increased data complexity and volume.
- There is a lack of comprehensive understanding of the practical implications of AI and ML in BI systems, particularly in the context of real-world business applications [40].
- Some studies are limited by their scope, such as focusing on specific industries or datasets, which limits the generalizability of the results.
- There is a lack of analysis on the context of collaboration within the AI research community.
- Some research has a limited analysis of the connections between DSS and BI&A, which indicates that some foundational knowledge is not being applied.
- There is a need for more empirical validation of proposed insights related to AI and ML in BI systems.

VI. Future Directions

A. *Technological Advances*

Future developments will likely focus on enhancing the capabilities of AI and ML in BI to move beyond descriptive analytics to predictive and prescriptive approaches [41]. Adding XAI to BI systems improves the transparency of AI decision-making processes and makes them more auditable to users. The analysis seeks to understand fully integrated AI and ML applications with blockchain and IoT technologies to build more powerful BI systems. AI and ML developers work to establish new methods for processing real-time data and analyzing information dynamically to support reactive business choices. The productive enhancement of AI and ML systems concerns their ability to detect anomalies and prevent fraud within various corporate sectors. AI, together with ML, enables improved data visualization methods that help business users obtain a clear understanding of their insights. Companies need to progress their development of AI models and ML algorithms to enhance prediction and forecasting capabilities.

B. *Research Opportunities*

- Additional study must be conducted to understand how AI and ML affect BI application practices throughout different industries and business circumstances.
- A thorough exploration of ethical factors must be conducted regarding AI and ML's usage in decision-support systems.
- The investigation of AI-human intelligence teamwork for better business decisions requires additional study.
- Studies must focus on determining optimal procedures for managing AI-based business model implementation processes.
- Research calls for ongoing analyses that trace AI and ML's effects on business model generation and business output improvement.
- Exploration of AI and ML applications to improve supply chain resilience.
- Further studies are needed to delve into niche areas of AI marketing
- More research is needed to understand the impact of AI on B2B marketing.
- Research on the applications of AI in the public sector.

C. *Practical Implications*

- Companies achieving competitive leadership through data analysis enhancement and decision-making improvements should invest in AI and ML-based BI systems.
- Business organizations must employ AI and ML for automatic data analysis because this practice reduces operational costs and increases operational efficiency.
- Through AI, as well as ML, predictive analytics companies achieve better inventory control and customer traffic management and market targeting support.

- Businesses that implement AI and ML technologies will enhance their customer satisfaction with personalized recommendation systems.
- Organizations must employ real-time analysis technologies for their market-sensitive operations.
- Organizations using AI-based business intelligence systems gain more effective abilities to find and stop fraudulent activity.
- Organizations need to implement AI-programmed data visualization tools that enhance the visibility of intricate dataset information.
- The workforce of companies must undergo training to enhance their capabilities of understanding and implementing AI and ML-based BI systems.

D. Overall Trends and Evolution

The implementation of AI and ML within BI systems produces substantial changes from static reporting to predictive and prescriptive analytics systems. The approach of traditional BI consisted of descriptive analytics for past data analysis, yet AI-pushed BI specializes in future trend prediction and decision-making proactivity [35]. Organizations now use AI and ML to analyze data better and detect unique patterns along with trends between variables that traditional methods fail to reveal [42]. The business environment drives the transformation because organizations need to manage growing data complexity and volume [43].

VII. Conclusion

This study offers three main contributions. First, it summarizes the existing research about AI and ML for the field's development in the past decade. Second, through the bibliometric approach, it represents the trends of AIML research. Third, it presents future research directions.

A. Research Implications

Research demonstrates that AI and ML have grown fundamental to improve business intelligence systems because it delivers extensive knowledge about the field's development throughout the past decade. The research study offers an extensive summary that details fundamental patterns alongside influential experts, while describing main subject areas and indicates areas where additional study can be conducted next. These findings benefit experts working with BI systems in addition to scholars who work with AI and ML integration for BI systems. According to this research, investigators proved that Business Intelligence moved from initial reporting functions towards developing sophisticated systems capable of delivering predictive and prescriptive capabilities essential for business success. After 2019, the number of publications in this field has grown significantly because these technologies have become essential for strategic decision-making.

This study is constrained by its limited dataset and review scope, highlighting the necessity for more extensive, in-depth, and longitudinal research to enhance future comprehension of AI-driven business intelligence.

B. Future Directions

The current research acknowledges several methodological limitations that provide clear avenues for future work. These include the study's confined scope to peer-reviewed articles within a specific ten-year timeframe (2014 to 2024) from only four major information sources, which inherently means it does not represent every published study in the field. Additionally, the analysis method employed presented constraints in fully understanding research findings in their complete context and depth, and the search criteria used had the potential to omit other essential relevant studies. The absence of detailed analysis of individual studies further limited the accuracy of the investigated results.

These limitations suggest that future research should expand the scope of the work to include better data and the analysis of full-text resources to facilitate the comprehension of the multifaceted nature of the domain. More studies are also recommended on the application of AI and Machine Learning within Business Intelligence in other sectors and business settings, mainly focusing on the application of these technologies. Future studies should attempt to resolve the gaps already mentioned, particularly on the ethics of AI in BI and the need to cultivate the synergy of AI with human intelligence and the design of effective frameworks for its application. There is also a demand for more research on the role of AI and ML in business, particularly in the areas of data visualization and explainable AI, to improve decision-making. Finally, more would be gained from AI and ML in business through research in the form of longitudinal studies.

References

[1] M. Soori *et al.*, "AI-based DSS in Industry 4.0," *J. Econ. Technol.*, 2024.

[2] Z. N. Jawad and V. Balázs, "ML-driven optimization of ERP systems," *Beni-Suef Univ. J. Basic Appl. Sci.*, vol. 13, 2024. doi: 10.1186/s43088-023-00460-y.

[3] G. P. Selvarajan, "Augmenting BI with AI," *Int. J. All Res. Educ. Sci. Methods*, vol. 11, no. 10, pp. 2121–2132, 2023.

[4] V. Hajipour, S. Hekmat, and M. Amini, "AI-as-a-service business plan," *Decis. Anal. J.*, vol. 8, p. 100302, 2023. doi: 10.1016/j.dajour.2023.100302.

[5] S. Armenia, E. Franco, F. Iandolo, G. Maielli, and P. Vito, "Zooming in and out the landscape: Artificial intelligence and system dynamics in business and management," *Technol. Forecast. Soc. Change*, vol. 200, p. 123131, Dec. 2023. doi: 10.1016/j.techfore.2023.123131.

[6] J. Rana and Y. Daultani, "Mapping AI/ML in supply chain digital transformation," *Oper. Manag. Res.*, vol. 16, no. 4, pp. 1641–1662, 2023. doi: 10.1007/s12063-022-00335-y.

[7] A. Madanaguli *et al.*, "AI capabilities for circular business models," *Technol. Forecast. Soc. Change*, vol. 200, p. 123189, 2023. doi: 10.1016/j.techfore.2023.123189.

[8] S. Chowdhury *et al.*, "AI-employee collaboration and business performance," *J. Bus. Res.*, vol. 144, pp. 31–49, 2022. doi: 10.1016/j.jbusres.2022.01.069.

[9] P. Jorzik *et al.*, "AI-driven business model innovation," *J. Bus. Res.*, vol. 182, p. 114764, 2024. doi: 10.1016/j.jbusres.2024.114764.

[10] G. Recupito *et al.*, "Technical debt in AI-enabled systems," *J. Syst. Softw.*, vol. 216, p. 112151, 2024. doi: 10.1016/j.jss.2024.112151.

[11] G. Phillips-Wren, M. Daly, and F. Burstein, "Reconciling BI, analytics and DSS," *Decis. Support Syst.*, vol. 146, p. 113560, 2021. doi: 10.1016/j.dss.2021.113560.

[12] J. Robertson *et al.*, "Managing change when integrating AI into retail value chains," *J. Bus. Res.*, vol. 189, p. 115198, 2023. doi: 10.1016/j.jbusres.2025.115198.

[13] E. Peretz-Andersson *et al.*, "AI implementation in manufacturing SMEs," *Int. J. Inf. Manag.*, vol. 77, p. 102781, 2024. doi: 10.1016/j.ijinfomgt.2024.102781.

[14] A. Shapovalova *et al.*, "Modernization of accounting and auditing using digital tools," *Financial and Credit Activity*, vol. 4, no. 51, pp. 33–52, 2023. doi: 10.55643/fcaptp.4.51.2023.4102.

[15] A. Kassa *et al.*, "AI techniques for enhancing supply chain resilience," *Comput. Ind. Eng.*, vol. 186, p. 109714, 2023. doi: 10.1016/j.cie.2023.109714.

[16] K. M. Toffaha, M. C. E. Simsekler, and M. A. Omar, "AI and DSS in pressure injury prediction," *Artif. Intell. Med.*, vol. 141, p. 102560, 2023. doi: 10.1016/j.artmed.2023.102560.

[17] R. Raman *et al.*, "Unveiling Dynamics of AI applications: A review of reviewsusing scientometrics and BERTopic modeling," *J. Innov. Knowl.*, vol. 9, p. 100517, 2024. doi: 10.1016/j.jik.2024.100517.

[18] R. Han *et al.*, "AI in business-to-business marketing," *Ind. Manag. Data Syst.*, vol. 121, no. 12, pp. 2467–2479, 2021. doi: 10.1108/IMDS-05-2021-0300.

[19] A. Haleem *et al.*, "AI applications for marketing," *Int. J. Intell. Netw.*, vol. 3, pp. 119–132, 2022. doi: 10.1016/j.ijin.2022.08.005.

[20] J. L. Ruiz-Real *et al.*, "AI in business and economics research," *J. Bus. Econ. Manag.*, vol. 22, no. 1, pp. 98–117, 2021. doi: 10.3846/jbem.2020.13641.

[21] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, "Artificial intelligence for decision making in the era of big data," *Int. J. Inf. Manag.*, vol. 48, pp. 63–71, 2019. doi: 10.1016/j.ijinfomgt.2019.01.021.

[22] Y. K. Dwivedi *et al.*, "So what if ChatGPT wrote it?," *Int. J. Inf. Manag.*, vol. 71, p. 102642, 2023. doi: 10.1016/j.ijinfomgt.2023.102642.

[23] S. Batisti and P. van der Laken, "History evolution and future of big data and analytics," *Br. J. Manag.*, vol. 30, no. 2, pp. 229–251, 2019.

[24] A. Di Vaio, R. Hassan, and C. Alavoine, "Data intelligence & analytics in public sector decision-making," *Technol. Forecast. Soc. Change*, vol. 174, p. 121201, 2021. doi: 10.1016/j.techfore.2021.121201.

[25] Y. Chen, C. Li, and H. Wang, "Big data and predictive analytics for business intelligence," *Forecasting*, vol. 4, no. 4, pp. 767–786, 2022. doi: 10.3390/forecast4040042.

[26] G. G. James *et al.*, "Optimizing BI using big data and ML," *J. Inf. Syst. Informatics*, vol. 6, no. 2, pp. 1215–1236, 2024.

[27] S. Kumar, W. M. Lim, U. Sivarajah, and J. Kaur, "AI and blockchain integration in business," *Inf. Syst. Front.*, vol. 25, no. 2, pp. 871–896, 2023. doi: 10.1007/s10796-022-10279-0.

[28] N. C. Eli-Chukwu, J. M. Aloh, and C. O. Ezeagwu, "AI applications in cellular networks," *Eng. Technol. Appl. Sci. Res.*, vol. 9, no. 4, pp. 4504–4510, 2019. doi: 10.48084/etasr.2788.

[29] I. Katib *et al.*, "Probabilistic neural network–based enterprise risk management," *Sci. Rep.*, vol. 14, p. 22293, 2024. doi: 10.1038/s41598-024-73876-w.

[30] V. Gooljar *et al.*, "Sentiment-based predictive models for online purchases," *J. Big Data*, vol. 11, 2024. doi: 10.1186/s40537-024-00947-0.

[31] A. Al-Okaily, A. P. Teoh, M. Al-Okaily, M. Iranmanesh, and M. A. Al-Betar, "The efficiency measurement of business intelligence systems in the big data-driven economy: A multidimensional model," *Inf. Discov. Deliv.*, vol. 51, no. 4, pp. 404–416, Oct. 2023. doi: 10.1108/IDD-01-2022-0008.

[32] R. S. Namwad *et al.*, "Optimizing inventory management with seasonal forecasting," *J. Eur. Syst. Automatisés*, vol. 57, no. 4, pp. 1091–1102, 2024. doi: 10.18280/jesa.570416.

[33] S. Maddula *et al.*, "Leveraging AI and reciprocal symmetry for BI," *Asian J. Appl. Sci. Eng.*, vol. 8, no. 1, pp. 73–84, 2024.

[34] A. Fareed, F. De Felice, A. Forcina, and A. Petrillo, "Advanced digital technologies for sustainability in logistics," *Sustain. Futures*, vol. 8, p. 100278, 2024. doi: 10.1016/j.sftr.2024.100278.

[35] N. A. Alghamdi, A. Al-Baity, and H. H., "Augmented analytics driven by AI: A digital transformation beyond business intelligence," *Sensors*, vol. 22, no. 20, 2022. doi: 10.3390/s22208071.

[36] M. Wu and X. Qin, "AI-based smart business management using ML," *Entertain. Comput.*, vol. 51, p. 100724, 2024. doi: 10.1016/j.entcom.2024.100724.

[37] R. Bogue, "The role of machine learning in robotics," *Ind. Robot*, vol. 50, no. 2, pp. 197–202, 2023. doi: 10.1108/IR-11-2022-0279.

[38] S. Bauskar, "Business analytics in enterprise system based on application of artificial intelligence," *Int. Res. J. Mod. Eng. Technol. Sci.*, vol. 4, no. 1, pp. 1861–1870, 2022.

[39] S. Ghosh, "Developing AI capabilities for business model innovation," *J. Eng. Technol. Manag.*, vol. 75, p. 101851, 2024. doi: 10.1016/j.jengtecman.2024.101851.

[40] M. Azmi, A. Mansour, and C. Azmi, "A context-aware empowering business with AI: Case of chatbots in BI systems," *Procedia Comput. Sci.*, vol. 224, pp. 479–484, 2023. doi: 10.1016/j.procs.2023.09.068.

[41] N. Rane *et al.*, "BI and analytics with AI and ML," *SSRN*, 2024. doi: 10.2139/ssrn.4831920.

[42] M. Aslam, D. Segura-Velandia, and Y. M. Goh, "A conceptual model framework for XAI requirement elicitation," *IEEE Access*, vol. 11, pp. 108080–108091, 2023. doi: 10.1109/ACCESS.2023.3315605.

[43] E. Eboigbe *et al.*, "Business intelligence transformation through AI and data analytics," *Eng. Sci. Technol. J.*, vol. 4, no. 5, pp. 285–307, 2023.