From Insights to Trust: A Review of AI-Driven Business Analytics Literature

Alina Cornelia LUCHIAN
Bucharest University of Economic Studies, Bucharest, Romania
luchianalina24@stud.ase.ro

Vasile Alecsandru STRAT
Bucharest University of Economic Studies, Bucharest, Romania
vasile.strat@bbs.ase.ro

Ovidiu JIANU
POLITEHNICA Bucharest, Bucharest, Romania
ovidiu.jianu@stud.acs.pub.ro

Monica DRAGOICEA
POLITEHNICA Bucharest, Bucharest, Romania
monica.dragoicea@upb.ro

Abstract. *This paper provides a comprehensive review of the application of artificial intelligence (AI) in business analytics (BA) with a focus on trust and transformative impacts. Employing topic modeling and PRISMA as methods for literature review, a thematic analysis of 61 academic articles published between 2019 and 2024 was conducted, uncovering key trends in trust, decision-making, data- driven processes, and AI-driven transformations. The study identifies five primary themes: the integration of AI in business intelligence and machine learning (ML); organizational strategies for innovation, the role of big data in education and skills development; methodological advancements in AI applications; customer adoption of AI-driven tools; and the broader implications of AI in Business Analytics. Sentiment analysis reveals predominantly positive perspectives on AI's transformative potential, though challenges such as organizational resistance, skill gaps, and methodological limitations persist. This review highlights the critical need for interdisciplinary research to address these challenges and foster trust in AI-driven business analytics.*

Keywords: business analytics, artificial intelligence, machine learning, trust, topic modelling, data-driven transformation.

Introduction

The adoption of artificial intelligence (AI) and machine learning has revolutionized business analytics (BA), enabling organizations to derive insights and make strategic decisions starting from data. While AI enhances decision-making processes, its integration requires alignment with organizational goals and trust-building principles like transparency, accountability, and reliability.

Business organizations now use machine learning algorithms and artificial intelligence technologies to advance business analytics and improve their decision-making processes (Kaggwa et al., 2024). This new perspective on data-driven transformation has completely changed the way they gather information, decide what to do, and develop business strategies (Brink et al., 2024; Badmus et al., 2024; Gómez-Caicedo et al., 2022). As both analytics and data are increasingly defining and refining decision making in modern organizations (Power et al., 2018), business

DOI: 10.2478/picbe-2025-0017

analytics (BA) advances the discourse on leveraging value from data by using various tools, methods, and models for data analysis, to extract insights from the data and make better informed decisions (Raghupathi & Raghupathi, 2021; Baabdullah, 2024; Neiroukh et al., 2024).

However, the integration of AI technologies into decision-making processes in business organizations should not occur in isolation (Kulkov et al., 2024), (Groenewald et al., 2024). Rather, it should be harmonized with other critical domains such as innovation, education, and organizational strategy (Adama et al., 2024). These processes require not only technological advancements, but also the development of improved theoretical frameworks to ensure alignment with broader organizational goals and social expectations (Borsatto et al., 2024; Costa, 2024) while building trust on fairness and accountability along the whole data analytics life cycle (Osasona et al., 2024; Odejide & Edunjobi, 2024). Nonetheless, the boundaries between these domains remain fluid and poorly defined, underscoring the need for a comprehensive study. Such an investigation would uncover opportunities, identify challenges, and pinpoint areas of impact, providing a foundation for establishing clearer frameworks. In addition, it would pave the way for future research directions, facilitating the responsible and effective adoption of AI technologies in interconnected domains.

The aim of this article is to evaluate how trust in AI-based decision-making processes can be attained, which requires a deliberate focus on transparency, accountability, and reliability throughout the entire analytics lifecycle. Henceforth, to achieve this, topic modeling is employed to uncover thematic trends and key challenges associated with building trust and understanding the transformative role of AI in the business analytics domain. Section 2 evaluated recent work on this domain. Section 3 presents our working methodology for data collection and structuring. Section 4 presents and analyses the results of the topic modeling process, and Section 5 concludes the paper.

Literature review

Recent research in business analytics has increasingly focused on the integration of machine learning and artificial intelligence (AI) to enhance decision-making processes (East, 2024), for improving the performance of information systems (Alduweib et al., 2024), and to evaluate trust in AI-assisted decision making (Vereschak et al., 2021; Tiwari, 2023; Soundararajan & Shenbagaraman, 2024).

Some studies have highlighted the role of Automated Machine Learning (AutoML) in democratizing AI adoption, allowing non-technical stakeholders to leverage advanced analytical tools effectively (Kharat & Mathur, 2023; Salehin, 2024). A recent study (Schmitt, 2023) showed that the new developments in (AutoML) have demonstrated great promise in addressing the difficulties brought on by the expanding need for BA applications of machine learning (ML). The study conducted that the new developments play a crucial role in bridging the gap between the supply and demand of ML expertise, promoting the integration of AI-driven solutions in a highly competitive and rapidly digitalizing marketplace.

Various works emphasize the importance of explainability and transparency in these automated systems, as trust remains a pivotal factor in their adoption (Sajid, 2025; Amirineni, 2024). Explainability and model interpretability in AI-based systems transcends application domains, while the AI’s transformative potential in predictive and prescriptive analytics showcasts its ability to identify patterns, simulate scenarios, and optimize strategies in various dynamic business environments, such as manufacturing (Colosimo & Centofanti, 2022; Stradowski &

Madeyski, 2024), financing (Hasan et al., 2024; Park et al., 2021), or information governance (Olateju et al., 2024), to name but a few.

However, challenges such as data quality, algorithmic bias, and the ethical implications of data-drive, AI-based decision-making continue to be active areas of investigation, underscoring the need for robust frameworks that balance innovation with accountability (Ali et al., 2023; Paramesha et al., 2024; Giudici et al., 2024; Chander et al., 2024).

Methodology

This section presents the methodologies that have been employed to conduct a thematic analysis of relevant papers retrieved from the Web of Science (WoS) database. The primary objective of this investigation is to use topic modeling approaches to find key concepts about trust, decision-making, data-driven processes, and the role of AI in business analytics (BA), using as a software tool *SAS Visual Text Analytics in SAS Viya*©. At the same time, we applied the PRISMA methodology (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) as being widely used to ensure transparency and rigor in systematic literature reviews. Hence, the PRISMA guidelines were used as part of this research to make the process of the systematic review transparent and complete. We begin by outlining *the topic modeling methodology*, detailing the steps involved in the process.

Data collection

The articles have been retrieved within the WoS database, and the following query has been applied:

```
TS = (("business analytics") AND ("artificial intelligence" OR "AI") AND
("trust*" OR "decision*" OR "data*" OR "data-driven" OR "AI-driven" OR
"transformation")) AND PY = (2019-2024).
```

The search covered both peer-reviewed journal articles and conference papers, and it has been limited to those published between January 1, 2019, and November 21, 2024. To ensure the relevance and quality of the dataset, only articles written in English have been selected. After excluding papers that were not directly related to the study's focus and duplicates, a final selection of 61 out of 100 articles has been selected for the analysis. The papers selected highlight topics like trust, decision-making, and data-driven transformation, and they reflect a variety of perspectives on the use of AI in BA.

Figure 1 illustrates the distribution of document and publication types within the selected scientific papers. Among the documents included, proceeding papers (conference papers - C) account for 15%, while most publications are journal articles (J).

Within journal publications, 66% have been categorized as standard articles, 8.2% as articles with early access, and 11% as review articles. This distribution highlights the predominance of traditional journal articles in the dataset, followed by a significant but smaller representation of review articles and conference papers, with early access articles forming the smallest proportion of journal types.

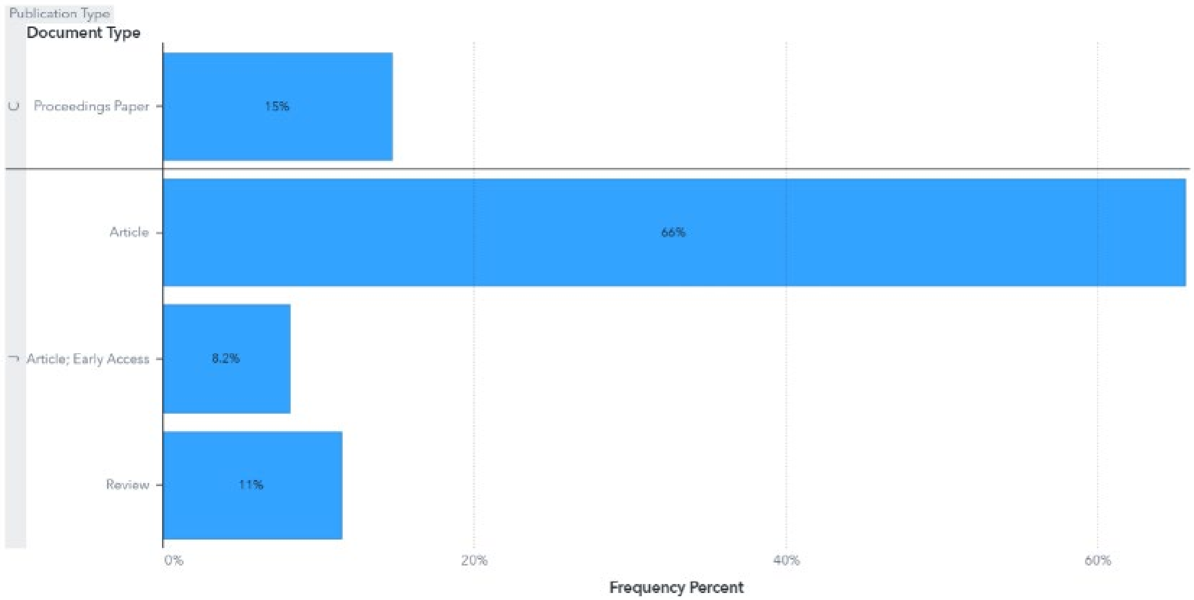

Figure 1. The distribution of document and publication types in selected scientific papers
Source: Authors' own research results/contribution.

A word cloud representation of the research areas from the selected papers has been illustrated in Figure 2, emphasizing the main study domains that are represented in it. The most common research fields have been identified as "Business & Economics" and "Computer Science" and the size of the terms reflects their frequency. This visualization provides an overview of the interdisciplinary focus of the selected papers, highlighting the contributions of various academic topics.

Figure 2. Word cloud representation of research areas from the selected papers
Source: Authors' own research results/contribution.

Figure 3 shows advances in research interest in AI-driven business analytics by showing the frequency of publications by year for different document categories. For document type

"Article", there is a slight increase in research interest from 2019 to 2024, reaching a peak in 2022 with 19.67% of the total publications and maintaining interest in 2024 at 14.75%. Similarly, for document type "Article; Early Access", 2024 marks a value of 6.56%. In contrast, document types such as "Proceedings Paper" and "Review" did not exhibit a significant increase in frequency over the analyzed period, suggesting a relatively stable but less dynamic presence in literature.

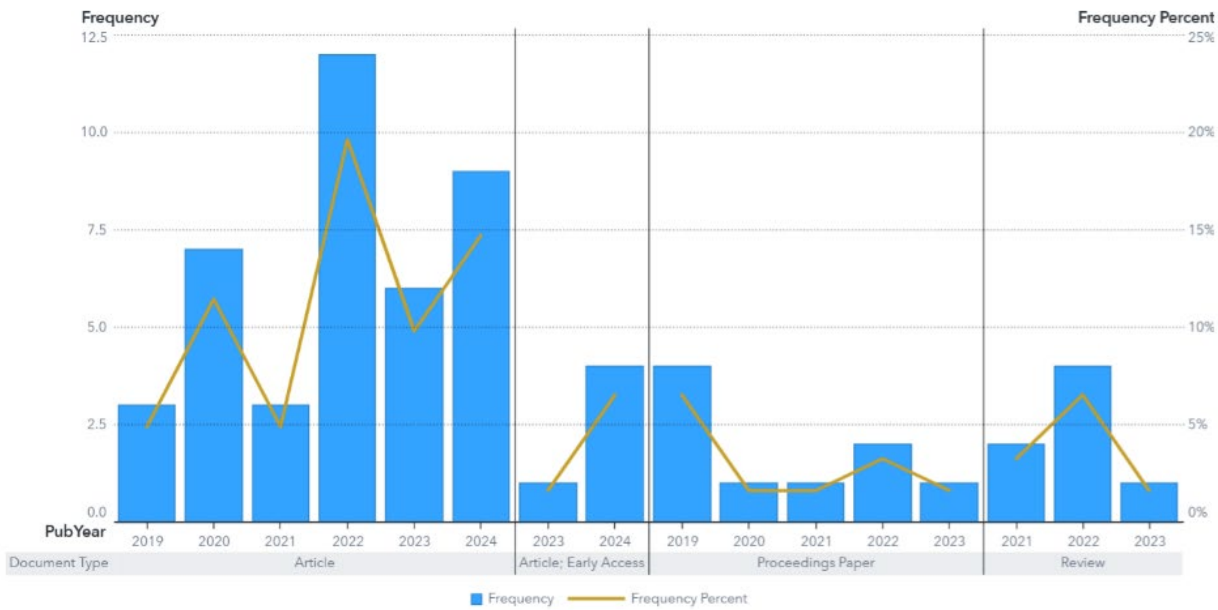

Figure 3. Frequency of selected papers by publication year and document type
Source: Authors' own research conducted in SAS Visual Analytics©.

Processing the data
To ensure the quality and consistency of the dataset, several preprocessing steps have been applied to get the textual data ready for topic modeling. The workflow, depicted in Figure 4, consists of the following sequential steps:

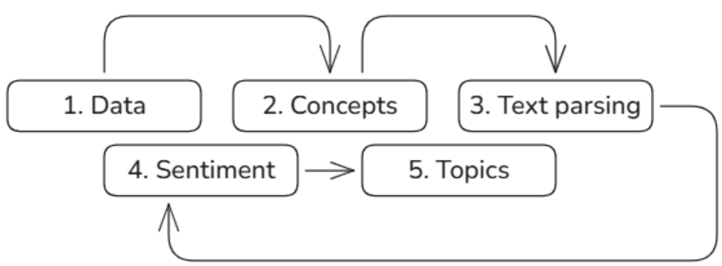

Figure 4. Data processing pipeline, created in SAS Visual Analytics©
Source: Authors' own research.

Data Preparation
The dataset containing abstracts and unique IDs have been imported and structured to ensure compatibility with the modeling process.

Concept Identification
Key concepts within the abstracts have been identified, serving as a foundation for text analysis by highlighting meaningful terms and phrases. The average number of matches per document in Figure 5 depicts the amount of information extraction performed by the concept inside each document where it matches.

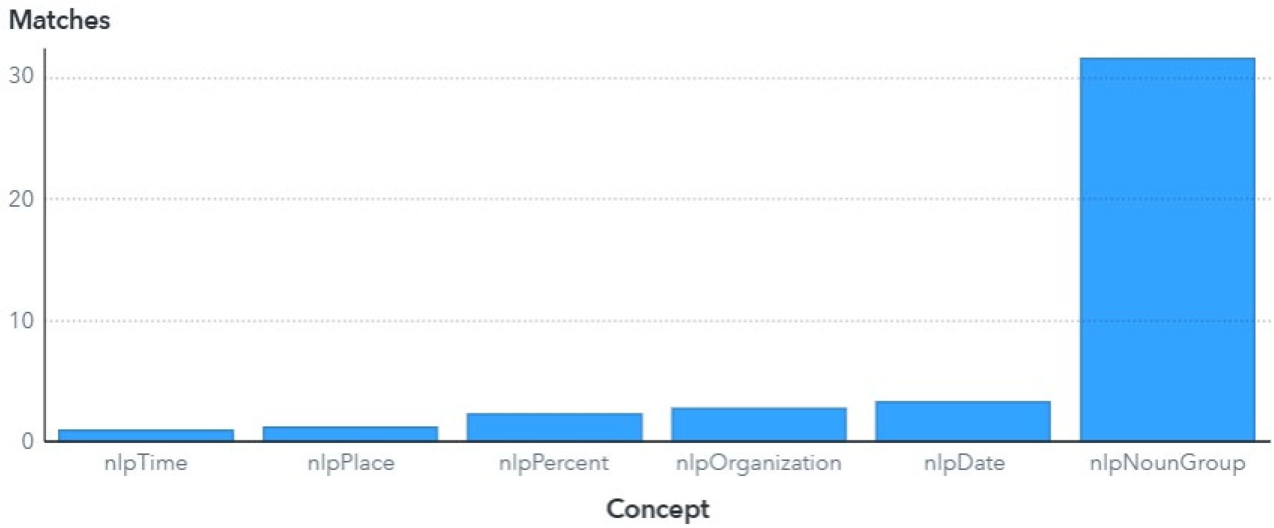

Figure 5. The average number of matches per document
Source: Authors' own research SAS Visual Analytics©.

In this data set, for example, when nlpDate matches in a document, it matches 3.33 times on average as also shown in Table 1.

Table 1. The average number of matches per document and the meaning of each concept

Concept	Matches	Description
nlpTime	1	Temporal expressions or references
nipple	1.25	Geographical locations mentioned in the text
nlpPercent	2.33	Percentage values
nlpOrganization	2.8	References to organizations, institutions, or groups
nlpDate	3.33	Specific calendar dates
nlpNounGroup	31.56	Significant noun phrases

Source: Authors' own research.

The calculation of the average number of matches per document does not include documents where the match count is zero for that concept. This aids in prioritization during the model's concept development process when a concept reaches the appropriate level of depth.

Text Parsing
The text parsing step processed the abstracts, filtering irrelevant or redundant words and breaking the text into standardized tokens to improve model accuracy. The text has been standardized and cleaned to remove unnecessary parts of the text. This involved the removal of stopwords (common

words such as "and", "or" and "the") that do not contribute meaningful information for the analysis of the text. Additionally, to preserve consistency and prevent treating words with different cases (such as "AI" and "ai") as distinct keywords, all text has been also transformed to lowercase. After that, tokenization has been utilized to divide the content into distinct words or significant phrases and reduce words to their most basic forms (e.g. "decisions" to "decision") so that related phrases can be grouped together. Irrelevant elements such as punctuation, numerical values and non-alphabetic characters have been removed to enhance the focus on core content.

Figure 6 presents a visual summary of the terms identified during text parsing, categorizing each term by its assigned role label. The bar heights in the report represent the frequency of each role type across the dataset. The most frequently occurring roles are nouns (N) and verbs (V), which together account for 43.06% of the terms.

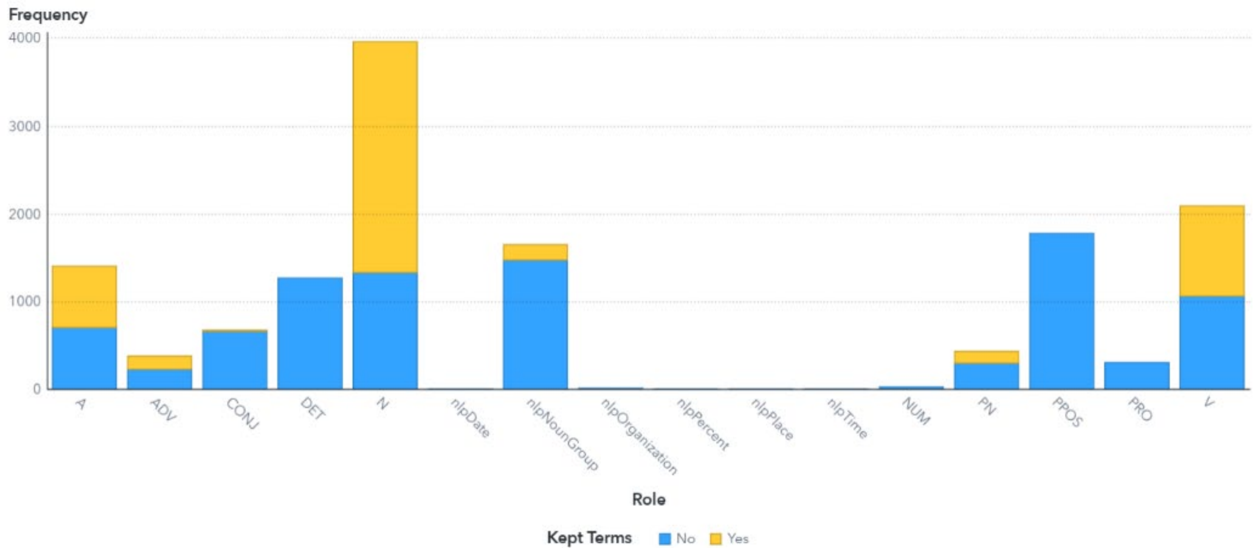

Figure 6. Role by frequency, created in SAS Visual Analytics©

Source: Authors' own research.

The bars in the chart illustrate the proportion of terms retained versus those excluded for each role, with the two colors representing these categories. In this case, 65.78% of the terms present in the data have been excluded from topic modeling. Terms have been removed either because they appeared on a stop list or failed to meet the frequency threshold specified by the minimum number of documents parameter.

Each identified role corresponds to either a part of speech (content or function word) or a concept. Parts of speech are categorized with labels such as N (noun), CONJ (conjunction), PN (proper noun), ADV (adverb), NUM (numeric), PUNC (punctuation), among others. Concepts may include noun groups (nlpNounGroup) as well as those defined and passed along from an upstream "Concepts" node in the analysis pipeline.

The dataset's patterns are highlighted by descriptive statistics in Table 2. The average sentence length, measured by the number of terms, is 27.91, with a range spanning from 3 to 117 terms. Similarly, the average document length is 230.64 terms, with lengths ranging from 106 to 542 terms. These statistics offer a high-level overview of the dataset, helping to identify any unexpected characteristics that may require further investigation.

Table 2. Descriptive statistics of sentence and document lengths

Measure	Terms in a sentence	Terms in a document
Minimum	3	106
Maximum	117	542
Mean	27.9147	230.6393

Source: Authors' own research.

Sentiment Analysis
Sentiment analysis has been applied to evaluate the emotional tone of the abstracts, classifying them into positive, negative, or neutral categories to complement topic identification.

Topic Modeling
Finally, the topic modeling process has been conducted to identify and extract the key themes embedded within the textual content of the abstracts of the selected 61 academic papers related to AI-driven business analytics. Feature selection has been performed by applying natural language processing (NLP) functions, emphasizing domain-specific terms such as "AI" "Business analytics" "trust" "data-driven" and "transformation". This ensured that only terms of thematic relevance have been kept in the preprocessed text. The tool used for topic modeling in this paper was SAS Viya, which employs LDA - an algorithm widely recognized as an effective method for uncovering hidden topics. It facilitated the identification of new themes based on the distribution of words across the documents, making it a suitable choice for this study.

The identified themes have been manually reviewed to ensure their relevance to the study's focus on trust, decision-making, data-driven processes, and AI transformation in BA.

As highlighted, our study employed a systematic review approach to evaluate the role of trust in AI-driven business analytics, guided by the *PRISMA© framework*. The following steps were undertaken.

Identification:
Articles were retrieved from the Web of Science (WoS) database using a comprehensive search query combining terms like "business analytics," "artificial intelligence," "trust," and "decision-making."

Search period: January 1, 2019, to November 21, 2024.
Results: 100 articles initially identified.
Exclusion criteria: non-English papers, duplicates, studies outside the scope of AI, trust, and decision-making in business analytics

Screening: titles and abstracts reviewed for relevance to the research focus
Number of Records After Duplicate Removal: 91.
Records excluded for irrelevance: 30.

Eligibility
Full-Text Articles Assessed: 61.
Exclusions:
Papers not addressing trust, AI, or business analytics.
Irrelevant methodological focus.

Inclusion:
Final dataset of 61 papers included in the review
Results analyzed for relevance to transparency, accountability, and reliability in AI-driven business analytics.

Results and discussions

The visual representation of the distribution of documents across topics within the dataset is depicted in Figure 7. The chart includes five bars representing the number of topics identified, while the sixth bar illustrates the documents that have been not assigned to any topic. The height of each bar corresponds to the number of documents allocated to each respective topic, with some documents potentially being assigned to multiple topics. Within the dataset, 23 documents (37.7%) have not been assigned to any topic. The bars representing each topic have been segmented by sentiment (positive, neutral, negative, or no sentiment), with color coding indicating the sentiment distribution for each topic.

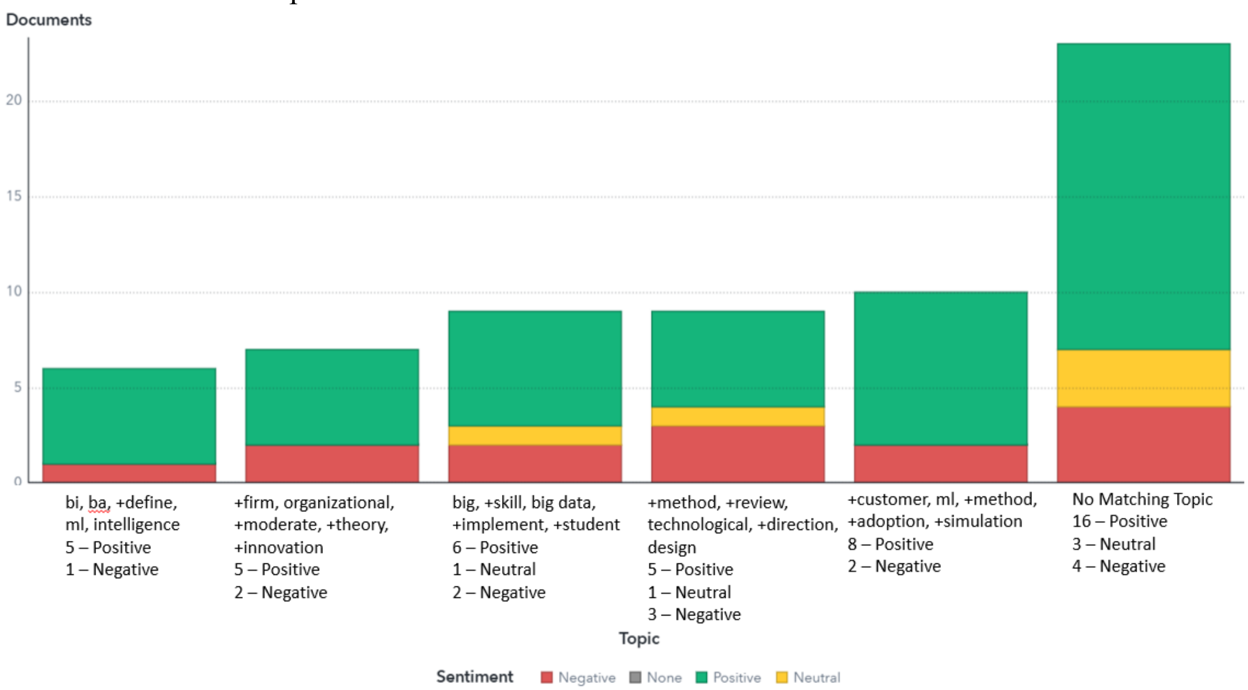

Figure 7. Distribution of documents across topics, created in SAS Visual Text Analytics©
Source: Authors' own research results/contribution.

Five themes have been identified with the use of topic modeling, offering insight into the different fields of study in AI-driven business analytics. In addition to representing the main subjects of interest, these themes may also capture the variety of emotions conveyed in literature, ranging from optimism to critical viewpoints. The terms represented by the "+" sign indicate the most influential terms in shaping the topics.

Theme 1: Business Intelligence (BI), Business Analytics (BA), Machine Learning (ML), and Artificial Intelligence (AI).

Identified topics: bi, ba, +define, ml, intelligence

Documents: Alghamdi & Baity, 2022; Žigienė et al., 2022; Ratia et al., 2019; Chen & Siau, 2020; Farooqi & Khozium, 2022; Alqhatani et al., 2022.

This theme focuses on the concepts of machine learning, business analytics, and business intelligence, emphasizing how these ideas are applied and integrated in business settings. Key terms such as "bi," "ba" "ml" and "intelligence" highlight the increasing significance of these technologies in improving data-driven decision-making and business management. This theme's sentiment is primarily positive (5 out of 6 documents), with only one document expressing negative emotion, indicating some challenges or concerns regarding the implementation of these technologies.

Theme 2: Firm Strategy, Organizational Theory, and Innovation.

Identified topics: +firm, organizational, +moderate, +theory, +innovation

Documents: Chaudhuri et al., 2024; Rana et al., 2022; Arias-Pérez et al., 2023, Chatterjee et al., 2024; Hayajneh et al., 2022; Chen & Siau, 2020, Zeebaree et al., 2020.

The second theme may suggest how businesses use AI technologies in their entire structure and strategy. Key terms such as "firm" "organizational" and "innovation" may highlight how AI promotes innovation and drives organizational change within a business. This theme also includes theoretical perspectives on how businesses adapt to technological advancements. Theoretical viewpoints on how companies adjust to technology developments are also included in this theme. While the sentiment is generally positive (5 documents), there are also negative sentiments (2 documents), reflecting critiques or challenges in applying AI within organizational frameworks.

Theme 3: Big Data, Skills Development, and Implementation in Education.

Identified topics: big, +skill, big data, +implement, +student

Documents: González-Carrasco et al., 2019; Amin & Rai, 2020; Wisniewski, 2020; Niederman, 2021; Sun & Huo, 2019; Anand & Mitchell, 2022, Karpa et al., 2023, Salvetti et al., 2022; Javed et al., 2021.

The integration of skills development and big data in education is the primary focus of this theme. The key terms such as "big data" "skill" and "student" suggest that the necessity to train and prepare the workforce to use AI and big data technologies are at the core of the theme. The positive sentiment predominates in this theme (6 documents), but some negative (2 documents) and neutral (1 document) sentiments highlight the difficulties in implementing AI and big data techniques in educational contexts.

Theme 4: Technological Methods, Reviews, and Future Directions.

Identified topics: +method, +review, technological, +direction, design

Documents: Giermindl et al., 2022, Neiroukh et al., 2024; Borges et al., 2021; Jabeur et al., 2024; Wissuchek & Zschech, 2024; Bender, 2024; Zeebaree et al., 2020; Thakral et al., 2023; Hoang, & Bui, 2023.

This subject focuses on reviews of current technologies and methodological advancements in AI-driven business analytics. Key terms such as "technological," "method" review" and "direction" imply that this theme includes reviews of current approaches, future development considerations, and the continuous evolution of techniques in the field. The sentiment in this topic is largely positive (5 documents), with some negative (3 documents) and neutral (1 document) sentiments. This suggests that there are still discussions about the topic and what methods need to be further improved.

Theme 5: Customer Adoption, Machine Learning, and Simulation.

Identified topics: +customer, ml, +method, +adoption, +simulation

Documents: Schmitt, 2023; Beinabadi et al., 2024; Rabia & Bellabdaoui, 2022; Gubela, et al., 2024; Sundaram et al., 2023; Biswas & Sanyal, 2019; Chen et al., 2024; Kaur et al., 2022; Alqhatani et al., 2022.

This theme focuses on the use of AI and machine learning techniques to understand and influence consumer behavior. Key terms such as "customer," "adoption" and "simulation" refer to studies on how AI can be used to improve decision-making, predict customer preferences, and maximize the customer experience. The sentiment is largely positive (8 documents), although negative sentiments (2 documents) suggest there are still challenges in customer adoption and the practical application of these methods.

The "No Matching Topic" bar refers to documents that did not align with any of the predefined topics. These papers might discuss more general or broader aspects of AI in business analytics that are difficult to classify. This category contains the largest number of documents, with 16 positive, 3 neutral, and 4 negative sentiments. Even though they don't relate to any specific subject, the documents in this theme are generally positive and offer a hopeful view of AI in BA.

Overall, these five themes are closely interconnected, demonstrating how AI and ML integration across different industries can drive innovation and future advancements, as such:

- **Theme 1** focuses on advanced technologies and data-driven decision-making, enabling businesses to make well-informed decisions.
- These technologies are also central to **Theme 2**, as they influence the entire business structure and strategy, as discussed in the paper.
- In **Theme 3** (Education), Big Data and skills development play a crucial role in preparing students for the increasing integration of AI and ML technologies across various industries.
- **Theme 4** explores how these technologies (e.g., from Theme 1) continue to evolve, offering insights into future developments.
- **Theme 5** highlights how technologies such as ML can be leveraged to analyze and predict customer behavior, a key factor in business success.

At the same time, we illustrate in Figure 8 the PRISMA© framework methodology applied in our research. ensures the systematic identification, selection, and analysis of studies, enhancing the transparency and replicability of the literature review process. Consequently, the method supports a robust evaluation of AI's role in business analytics, focusing on trust and its implications.

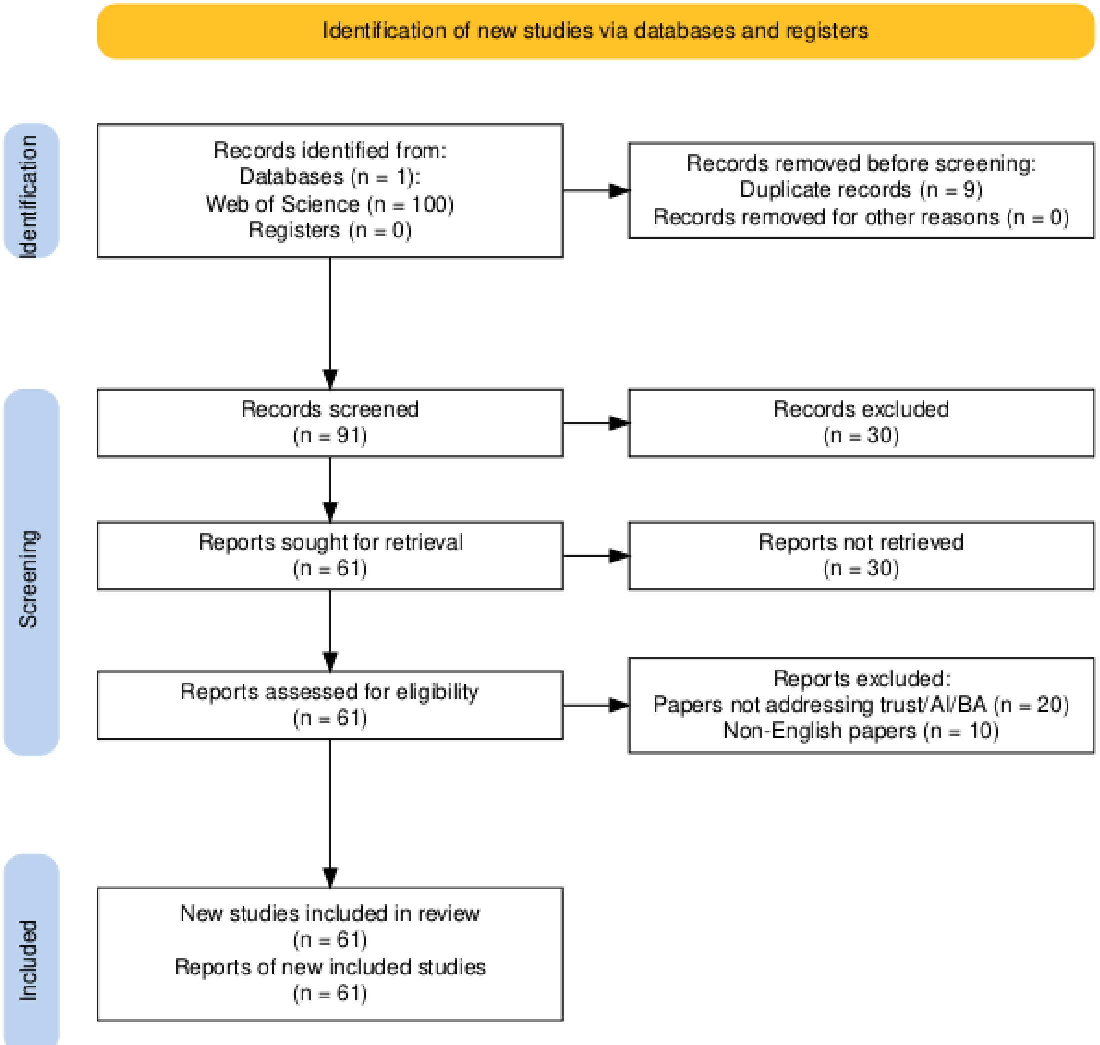

Figure 8. Prisma Flow Diagram ©for literature systematic review

Source: www. shribe.eu/prisma-literature-review and authors' own search.

Conclusion

By conducting the topic modeling and sentiment analysis on the selected dataset of scientific papers in an automatic way, five key thematic themes have been identified that highlight the complexity of research in the field of BA. In this study, we employed LDA within an automated data processing pipeline using SAS Viya Text Analytics. Our approach did not incorporate other NLP techniques such as word embeddings or transformer architectures. The preprocessing, topic extraction, and mapping of paper abstracts to topics were conducted entirely within SAS Viya, leveraging its built-in functionalities. Stopword removal and other text preprocessing steps followed the default configurations provided by the platform. This standardized pipeline ensures reproducibility and transparency within the SAS Viya environment.

The obtained results highlight the positive sentiment associated with these topics, reflecting the optimism and potential surrounding the transformative capabilities of AI in business analytics. However, the presence of negative and neutral sentiments across the identified themes underscores the multifaceted challenges and complexities involved in implementing AI technologies in real-world contexts. These challenges may include organizational resistance to change, skill gaps among employees, ethical concerns, and limitations in existing methodologies and technologies. Addressing these issues in future research is crucial for maximizing the benefits of AI while ensuring its sustainable and responsible adoption.

While this study provides insights by analyzing journal articles and conference papers, several limitations and potential biases should be acknowledged. The selection of these types of sources may exclude other types of publications, potentially omitting relevant studies. The limited number of papers analyzed may affect the generalizability of the findings, as a larger dataset could enhance robustness. Additionally, the focus on research published between 2019 and 2024 may overlook significant earlier contributions. The use of LDA for topic modeling presents challenges, such as selecting the optimal number of topics and ensuring interpretability. Lastly, restricting the analysis to English-language publications may exclude valuable research from other linguistic and regional contexts.

As further research, the emerging regulations and recommendations outlined in the EU AI Act and more specifically the very recent Artificial Intelligence Action Summit in Paris reshaping dramatically the European research directions on AI, in February 2025, must be taken into consideration in our further studies, as they provide critical guidelines for ethical, transparent, and trustworthy AI deployment. These regulatory frameworks will play a key role in shaping the adoption of AI technologies in business analytics and ensuring their alignment with societal and ethical values.

References

Adama, H.E., Popoola, O.A., Okeke, C.D., Akinoso, A.E.: Theoretical framework supporting it and business strategy alignment for sustained competitive advantage. International Journal of Management & Entrepreneurship Research 6(4), 1273-1287 (2024).

Alduweib, E., Arqoub, M. A., & Alromema, W. (2024, February). Automated Machine Learning for Information Management and Information Systems: An Overview. In 2024 2nd International Conference on Cyber Resilience (ICCR) (pp. 1-5). IEEE.

Alghamdi, N.A., Al-Baity, H.H.: Augmented analytics driven by ai: A digital transformation beyond business intelligence. Sensors 22(20), 8071 (2022)

Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., ... & Herrera, F. (2023). Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. Information fusion, 99, 101805.

Alqhatani, A., Ashraf, M.S., Ferzund, J., Shaf, A., Abosaq, H.A., Rahman, S., Irfan, M., Alqhtani, S.M.: 360 retail business analytics by adopting hybrid machine learning and a business intelligence approach. Sustainability 14(19), 11942 (2022)

Amin, D. M., & Rai, M. (2020). A Novel Framework for Enhancing QoS of Big Data. International Journal of Advanced Computer Science and Applications, 11(4).

Amirineni, S. (2024). Enhancing Predictive Analytics in Business Intelligence through Explainable AI: A Case Study in Financial Products. Journal of Artificial Intelligence General science (JAIGS) ISSN:3006-4023.

Anand, T., & Mitchell, D. (2022). Objectives and curriculum for a graduate business analytics capstone: Reflections from practice. Decision Sciences Journal of Innovative Education, 20(4), 235-245.

Arias-Pérez, J., Chacón-Henao, J., & López-Zapata, E. (2023). Unlocking agility: Trapped in the antagonism between co-innovation in digital platforms, business analytics capability and external pressure for AI adoption? Business Process Management Journal, 29(6), 1791-1809.

Baabdullah, A. M. (2024). The precursors of AI adoption in business: Towards an efficient decision-making and functional performance. International Journal of Information Management, 75, 102745.

Badmus, O., Rajput, S. A., Arogundade, J. B., & Williams, M. (2024). AI-driven business analytics and decision making. World Journal of Advanced Research and Reviews, 24(1), 616-633.

Beinabadi, H. Z., Baradaran, V., & Komijan, A. R. (2024). Sustainable supply chain decision-making in the automotive industry: A data-driven approach. Socio-Economic Planning Sciences, 95, 101908.

Bender, T. (2024). Towards a process selection method for embedded analytics. Information Systems and e-Business Management, 1-25.

Biswas, B., & Sanyal, M. K. (2019, January). Soft intelligence approaches for selecting products in online market. In 2019 9th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 432-437). IEEE.

Brink, A., Benyayer, L. D., & Kupp, M. (2024). Decision-making in organizations: should managers use AI? Journal of Business Strategy, 45(4), 267-274.

Borges, A. F., Laurindo, F. J., Spínola, M. M., Gonçalves, R. F., & Mattos, C. A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. International journal of information management, 57, 102225.

Borsatto, J. M. L. S., Marcolin, C. B., Abdalla, E. C., & Amaral, F. D. (2024). Aligning community outreach initiatives with SDGs in a higher education institution with artificial intelligence. Cleaner and Responsible Consumption, 12, 100160.

Chander, B., John, C., Warrier, L., & Gopalakrishnan, K. (2024). Toward trustworthy artificial intelligence (TAI) in the context of explainability and robustness. ACM Computing Surveys.

Chatterjee, S., Chaudhuri, R., & Vrontis, D. (2024). Does data-driven culture impact innovation and performance of a firm? An empirical examination. Annals of Operations Research, 333(2), 601-626.

Chaudhuri, R., Chatterjee, S., Vrontis, D., & Thrassou, A. (2024). Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. Annals of Operations Research, 339(3), 1757-1791.

Chen, Y., Rui, H., & Whinston, A. B. (2024). Conversation Analytics: Can Machines Read between the Lines in Real-Time Strategic Conversations? Information Systems Research.

Chen, X., & Siau, K. (2020). Business analytics/business intelligence and IT infrastructure: impact on organizational agility. Journal of Organizational and End User Computing (JOEUC), 32(4), 138-161.

Costa, E. (2024). Industry 5.0 and SDG 9: a symbiotic dance towards sustainable transformation. Sustainable Earth Reviews, 7(1), 4.

Colosimo, B. M., & Centofanti, F. (2022). Model interpretability, explainability and trust for manufacturing 4.0. In Interpretability for Industry 4.0: Statistical and Machine Learning Approaches (pp. 21-36). Cham: Springer International Publishing.

East, A., & Chastain, K. (2024). Automated Machine Learning: Revolutionizing Data Science and Decision-Making. Innovative Computer Sciences Journal, 10(1), 1-9.

European Commission Artificial Intelligence Act (2022). https://artificialintelligenceact.eu.

Farooqi, N. S., & Khozium, M. O. (2022). Implementation of Artificial Intelligence Based Analyzer Using Multi-Agent System Approach. Intelligent Automation & Soft Computing, 31(1).

Giermindl, L. M., Strich, F., Christ, O., Leicht-Deobald, U., & Redzepi, A. (2022). The dark sides of people analytics: reviewing the perils for organizations and employees. European Journal of Information Systems, 31(3), 410-435.

Giudici, P., Centurelli, M., & Turchetta, S. (2024). Artificial Intelligence risk measurement. Expert Systems with Applications, 235, 121220.

Gómez-Caicedo, M. I., Gaitán-Angulo, M., Bacca-Acosta, J., Briñez Torres, C. Y., & Cubillos Díaz, J. (2022). Business analytics approach to artificial intelligence. Frontiers in Artificial Intelligence, 5, 974180.

González-Carrasco, I., Jiménez-Márquez, J. L., López-Cuadrado, J. L., & Ruiz-Mezcua, B. (2019). Automatic detection of relationships between banking operations using machine learning. Information Sciences, 485, 319-346.

Groenewald, C. A., Groenewald, E., Uy, F., Kilag, O. K., Rabillas, A., & Cabuenas, M. H. (2024). Organizational Agility: The Role of Information Technology and Contextual Moderators-A Systematic Review. International Multidisciplinary Journal of Research for Innovation, Sustainability, and Excellence (IMJRISE), 1(3), 32-38.

Gubela, R. M., Lessmann, S., & Stöcker, B. (2024). Multiple treatment modeling for Target Marketing campaigns: A large-scale Benchmark Study. Information Systems Frontiers, 26(3), 875-898.

Hasan, M. R., Gazi, M. S., & Gurung, N. (2024). Explainable AI in Credit Card Fraud Detection: Interpretable Models and Transparent Decision-making for Enhanced Trust and Compliance in the USA. Journal of Computer Science and Technology Studies, 6(2), 01-12.

Hayajneh, J. A. M., Elayan, M. B. H., Abdellatif, M. A. M., & Abubakar, A. M. (2022). Impact of business analytics and π-shaped skills on innovative performance: Findings from PLS-SEM and fsQCA. Technology in Society, 68, 101914.

Hoang, T. G., & Bui, M. L. (2023). Business intelligence and analytic (BIA) stage-of-practice in micro-, small-and medium-sized enterprises (MSMEs). Journal of Enterprise Information Management, 36(4), 1080-1104.

Jabeur, S. B., Stef, N., & Arfi, W. B. (2024). Artificial intelligence for innovation: a bibliometric analysis and structural variation approach. International Journal of Innovation Management, 28(05n06), 2450020.

Javed Awan, M., Mohd Rahim, M. S., Nobanee, H., Munawar, A., Yasin, A., & Zain, A. M. (2021). Social media and stock market prediction: a big data approach. MJ Awan, M. Shafry, H. Nobanee, A. Munawar, A. Yasin et al.," Social media and stock market prediction: a big data approach," Computers, Materials & Continua, 67(2), 2569-2583.

Kaggwa, S., Eleogu, T. F., Okonkwo, F., Farayola, O. A., Uwaoma, P. U., & Akinoso, A. (2024). AI in decision making transforming business strategies. International Journal of Research and Scientific Innovation, 10(12), 423-444

Karpa, M., Kitsak, T., Domsha, O., Zhuk, O., Акімова, Л., & Akimov, O. (2023). Artificial intelligence as a tool of public management of socio-economic development: Economic systems, smart infrastructure, digital systems of business analytics and transfers.AD ALTA: Journal of Interdisciplinary Research, 13(1),13–20. https://doi.org/10.33543/1301341320

Kaur, R., Singh, R., Gehlot, A., Priyadarshi, N., & Twala, B. (2022). Marketing strategies 4.0: Recent trends and technologies in marketing. Sustainability, 14(24), 16356.

Kharat, R., Mathur, A.: Bridging the trust gap in machine learning automation: Enhancing end-user confidence through generative ai-driven explanations in natural language. In: Workshop on e-Business. pp. 126–138. Springer (2023)

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence-driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. Sustainable Development, 32(3), 2253-2267.

Liu, S., Liu, O., & Chen, J. (2023). A review on business analytics: definitions, techniques, applications and challenges. Mathematics, 11(4), 899.

Neiroukh, S., Aljuhmani, H. Y., & Alnajdawi, S. (2024, January). In the era of emerging technologies: discovering the impact of artificial intelligence capabilities on timely decision-making and business performance. In 2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS) (pp. 1-6). IEEE.

Niederman, F. (2021). Project management: openings for disruption from AI and advanced analytics. Information Technology & People, 34(6), 1570-1599.

Odejide, O. A., & Edunjobi, T. E. (2024). AI in project management: exploring theoretical models for decision-making and risk management. Engineering Science & Technology Journal, 5(3), 1072-1085.

Olateju, O., Okon, S. U., Olaniyi, O. O., Samuel-Okon, A. D., & Asonze, C. U. (2024). Exploring the concept of explainable AI and developing information governance standards for enhancing trust and transparency in handling customer data. Available at SSRN.

Osasona, F., Amoo, O. O., Atadoga, A., Abrahams, T. O., Farayola, O. A., & Ayinla, B. S. (2024). Reviewing the ethical implications of AI in decision making processes. International Journal of Management & Entrepreneurship Research, 6(2), 322-335.

Paramesha, M., Rane, N. L., & Rane, J. (2024). Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence. Partners Universal Multidisciplinary Research Journal, 1(2), 110-133.

Park, M. S., Son, H., Hyun, C., & Hwang, H. J. (2021). Explainability of machine learning models for bankruptcy prediction. Ieee Access, 9, 124887-124899.

Power, D. J., Heavin, C., McDermott, J., & Daly, M. (2018). Defining business analytics: an empirical approach. Journal of Business Analytics, 1(1), 40-53.

Rabia, M.A.B., Bellabdaoui, A.: A comparative analysis of predictive analytics tools with integrated what-if modules for transport industry. In: 2022 14th International Colloquium of Logistics and Supply Chain Management (LOGISTIQUA).pp. 1–6. IEEE (2022)

Raghupathi, W., & Raghupathi, V. (2021). Contemporary business analytics: An overview. Data, 6(8), 86.

Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2022). Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. European Journal of Information Systems, 31(3), 364-387.

Ratia, M., Myllärniemi, J., & Helander, N. (2019). The potential beyond IC 4.0: the evolution of business intelligence towards advanced business analytics. Measuring Business Excellence, 23(4), 396-410.

Salehin, I., Islam, M. S., Saha, P., Noman, S. M., Tuni, A., Hasan, M. M., & Baten, M. A. (2024). AutoML: A systematic review on automated machine learning with neural architecture search. Journal of Information and Intelligence, 2(1), 52-81.
Salvetti, F., Bertagni, B., Negri, F., Bersanelli, M., Usai, R., Milani, A., & De Rosa, D. (2022). At Your Best! Artificial Intelligence, People and Business Analytics, Highly Realistic Avatars, Innovative Learning and Development. In Innovations in Learning and Technology for the Workplace and Higher Education: Proceedings of 'The Learning Ideas Conference'2021 (pp. 280-289). Springer International Publishing.
Sajid, S., Arachchige, J. J., Bukhsh, F. A., Abhishta, A., & Ahmed, F. (2025). Building Trust in Predictive Analytics: A Review of ML Explainability and Interpretability. International Journal of Computing Sciences Research, 9, 3364-3391.
Schmitt, M.: Automated machine learning: Ai-driven decision making in business analytics. Intelligent Systems with Applications 18, 200188 (2023)
Soundararajan, R., & Shenbagaraman, V. M. (2024). Enhancing financial decision-making through explainable AI and Blockchain integration: improving transparency and trust in predictive models. Educational Administration: Theory and Practice, 30(4), 9341-9351.
Stradowski, S., & Madeyski, L. (2024). Interpretability/Explainability Applied to Machine Learning Software Defect Prediction: An Industrial Perspective. IEEE Software.
Sun, Z., & Huo, Y. (2019, January). A managerial framework for intelligent big data analytics. In Proceedings of the 2nd International Conference on Software Engineering and Information Management (pp. 152-156).
Sundaram, A., Abdel-Khalik, H. S., & Abdo, M. G. (2023). Preventing Reverse Engineering of Critical Industrial Data with DIOD. Nuclear Technology, 209(1), 37-52.
Thakral, P., Srivastava, P. R., Dash, S. S., Jasimuddin, S. M., & Zhang, Z. (2023). Trends in the thematic landscape of HR analytics research: a structural topic modeling approach. Management Decision, 61(12), 3665-3690.
Tiwari, R.: Explainable ai (xai) and its applications in building trust and understanding in ai decision making. International J. Sci. Res. Eng. Manag 7, 1–13 (2023)
Vereschak, O., Bailly, G., & Caramiaux, B. (2021). How to evaluate trust in AI-assisted decision making? A survey of empirical methodologies. Proceedings of the ACM on Human-Computer Interaction, 5(CSCW2), 1-39.
Wisniewski, H. S. (2020). What is Business with AI? Preparing Future Decision Makers and Leaders. Technology & Innovation, 21(4), 1-14.
Wissuchek, C., Zschech, P.: Prescriptive analytics systems revised: systematic literature review from an information systems perspective. Information Systems and e-Business Management pp. 1–75 (2024)
Zeebaree, M., Ismael, G. Y., Nakshabandi, O. A., Saleh, S. S., & Aqel, M. (2020). Impact of innovation technology in enhancing organizational management. Studies of Applied Economics, 38(4).
Žigienė, G., Rybakovas, E., Vaitkienė, R., & Gaidelys, V. (2022). Setting the grounds for the transition from business analytics to artificial intelligence in solving supply chain risk. Sustainability, 14(19), 11827.