



Review Article

The Rise of Conversational BI and NLP's Impact: A Systematic Literature Review

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Abstract: This systematic literature review explores the impact of Natural Language Processing (NLP) in developing Business Intelligence (BI) systems focusing on the rise of Conversational Business Intelligence (CBI). It seeks to determine how NLP can improve user accessibility, decision making, and options available in navigating integration concerns in BI frameworks. Using the PRISMA 2020 guidelines, the review examined 18 peer-reviewed studies presented in the period between 2019 and 2024 through the Google Scholar and the Saudi Digital Library. Inclusion criteria based on pre-set criteria of NLP's utilization in BI were applied to studies, and for their quality – methodological rigor and relevance, were considered. Findings had to be thematically grouped to handle issues of user accessibility, decision consequences and technical issues. NLP obviously increases BI accessibility with conversational interfaces that empower non-technical users, up to 30% more adoption rates in self-service systems. It enhances decision making using advanced analytics; sentiment analysis (85% accuracy) and predictive modeling (>95% accuracy) enable real time insights. However, scalability limitation, computational requirement and ethical issues such as bias and privacy call for strong solutions for CBI's effective deployment. NLP integration of BI systems creates transformative value in terms of organizational data application, but facing technical and ethical challenges, adoption is not an easy task. In future research, building of scalable architectures, domain-specific NLP applications and use of ethical frameworks should be considered for CBI systems to be accessible, efficient and trustworthy. These have an implication that calls for interdisciplinary activities in ensuring that technological innovation is matched with practical utility.

Keywords: Natural Language Processing (NLP); Business Intelligence (BI); BI Dashboards; Conversational BI; CBI;

1. Introduction

Organizations today generate data at an increasing rate, proportionately this data increases with the size of the organization[1]. Business Intelligence (BI) systems have become an important decision-making tool for organizations, because of this massive data growth including both structured and unstructured, that allowed them to generate valuable insights to guide strategic and operational decisions[2], [3]. BI systems allow organizations to work with analytical data and create insights for strategic and operational decisions

to maintain an edge in a changing market[4], [5]. Traditional BI systems maintain important status but face common usage problems with user accessibility[6]. The technical nature of interfaces together with static dashboards and SQL as query language creates exclusion barriers for users who lack technical skills when interacting with data[7], [8]. Over 70% of BI implementations fail due to poor user engagement and inaccessible interfaces[9], [10]. Organizations that aim for data accessibility and data democratization leadership need adaptable BI solutions because data democratization efforts continue expanding[11], [12], [13].

BI systems achieve their most promising solution through the integration of Natural Language Processing (NLP) which is an aspect of artificial intelligence[14]. A machine's ability to understand human language becomes possible with NLP, it enables both interpretation and generation of natural speech, that allows users to query the system through conversational dialogue[15]. The new system defines a complete transition from standard BI into Conversational Business Intelligence (CBI) through which users obtain accurate real-time information through verbal inquiries like "What were our Q1 sales figures"? [16]. The introduction of CBI signals a fundamental change in BI direction; it creates a system that offers rapid decision support and accessible to all users[16]. CBI, enriched with NLP, allows users to ask for data using plain language (for example, what were our Q1 sales figures?) providing real-time insights to accelerate the decision-making process[17]. The application enables multiple user groups besides technical stakeholders to become system supporters, which boosts overall adoption rates while facilitating instantaneous analytics needs for finance, healthcare, and retail operations[13], [16]. Research has analyzed each aspect of CBI over the past five years, but the literature has not been fully synthesized. The BI landscape requires better systematic investigation which addresses how NLP technology advances this field. The existing research fails to unite different advancements as well as challenges together with outcomes related to CBI systems[18], [19], [20].

This paper performs a Systematic Literature Review (SLR), articles included are between 2019 and 2024. Eighteen relevant studies have been viewed to construct a concise understanding of CBI systems. First, analyzes how NLP technology improves BI system for technical and non-technical users through easier data handling methods. And then evaluates CBI systems in two areas: data acquisition speed and real-time analytics capabilities in addition to their influence on operational decision speed. Also, focuses on recognizing main technical issues with NLP implementation that are faced in BI systems regarding scalability problems, ambiguous data, legacy system integration and multilingual support.

2. Background

Modern enterprises require better BI systems, because data-driven decision-making has increased their operational dependence on data-driven choices[21]. The features of traditional BI systems include structured dashboards with built-in reporting templates and dependence on Structured Query Language (SQL) and other query-building approaches[22], [23]. BI systems that traditionally were structured for technical users have a dashboard and SQL and thus exclude access which goes beyond technical users[24]. Organizations spend significant funds on BI infrastructure, but numerous organizations experience limited success in getting their users to adopt and engage with it [25], [26].

Recent NLP developments serve as solutions to address current dashboard and data interaction boundaries[27]. As part of Artificial Intelligence (AI), NLP serves as the fundamental investigation which develops methods for machines to understand human-level language activities[28]. NLP system integration into BI enabled the development of CBI through which users achieve analytical tasks through natural language queries that can be text-based or speech-based.[29] Deep learning found recognition through its key advancements, which led to the development of transformer-based architecture[30]. BERT (Bidirectional Encoder Representations from Transformers) uses its bidirectional attention mechanism together with analyzing sentence contexts from both sentence directions whereas GPT-3 (Generative Pretrained Transformer 3) demonstrates great proficiency in conducting few-shot learning and the dynamic response generation [31], [32]. These architectural systems achieved remarkable performance in question

answering and named entity recognition together with language inference tasks thus becoming optimal choices for BI domains that need to handle diverse user input formats and intentions[30], [31], [32].

The BI context makes use of NLP to deliver three fundamental features: including (1) semantic parsing for converting natural language questions into machine-executable queries, (2) intent recognition to detect user objectives and (3) entity recognition which defines data schema elements such as "sales in Q1" as sales table. Q1 [33], [34]. This system enables users without coding expertise to obtain BI through linguistic processing of data schema information and query syntax [25], [35]. Adopting CBI demands the solution of multiple technical obstacles in its implementation [16]. The main technical challenge in user input exists because of its ambiguous nature which becomes difficult to handle when multiple intents or domain-specific terms or vague references are present. A maturing set of context-aware systems that perform disambiguation and dialogue management needs to handle such complex matters within enterprise setups [36], [37]. Dynamic scalability presents a vital practical issue for NLP elements to process real-time requests against extensive database systems which may need supplementary caching components together with vector search approaches and symbolic-sub-symbolic hybrid architectural methods [38], [39].

3. Methodology

3.1. Search Strategy

The purpose of SLR was to provide an in-depth analysis of both CBI growth and NLP involvement in its development. The main purpose was to assess and combine research that explores the integration approaches and usability aspects and functional challenges of NLP applications in BI systems. Applying PRISMA 2020 procedures during the selection process [40]. An extensive research investigation through two academic databases: Google Scholar and the Saudi Digital Library (SDL). The search terms and strategy were constructed to capture the studies in the field of CBI and NLP (Table1).

Table 1: Search Strategy and Keywords

Search Components	Details
Databases Used	Saudi Digital Library, Google Scholar
Search Period	2019–2024
Keywords	"Conversational BI", "Business Intelligence", "Natural Language Processing in BI", "Business Intelligence Dashboards", "BI System"
Boolean Operators	AND, OR

3.2. Selection and Screening Process

The first search retrieved 56,123 records (19,200 in Google Scholar, 36,923 in SDL). A multi-stage screening strategy has been implemented to narrow studies according to predefined inclusion and exclusion criteria indicated in (Table 2).

The PRISMA 2020 flow diagram (Figure 1) demonstrates the screening levels:

- 30,654 duplicates.
- 523 identified as ineligible by automation tools.
- 2,930 excluded due to topic irrelevance.
- 2,308 filtered based on publication type.
- 4,689 removed based on publication year.
- 11,200 excluded for other miscellaneous reasons.

Table 2: Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Publication Type	Peer-reviewed journal articles, conference papers	Books, editorials, non-peer-reviewed reports, grey literature
Language	English	Non-English publications
Relevance	Studies focusing on NLP integration in BI or CBI systems	Studies unrelated to BI, NLP, or CBI
Publication Year	2019–2024	Published before 2019
Accessibility	Full-text accessible via institutional access or open access	Full-text unavailable
Methodology	Clear methodology (e.g., experimental, case study, systematic review)	Insufficient methodological clarity or purely theoretical without evidence

A total of 3,819 records remained for title and abstract review after the first stage of refinement. A 108 full-text articles became available for review after 3,711 documents were excluded because they lacked application to the research goals. Some articles remained inaccessible because of restricted access limitations. The total number of unavailable texts amounted to 79 publications. The assessment phase determined 29 full-text articles out of all selected documents. The application of inclusion and exclusion criteria led to the exclusion of 11 articles mainly because of insufficient methodological clarity and extensive length. Only 18 studies passed all requirements. The simplified visual summary (Figure 2) shows the record counts during each stage of screening in addition to the PRISMA flow diagram (Figure 1).

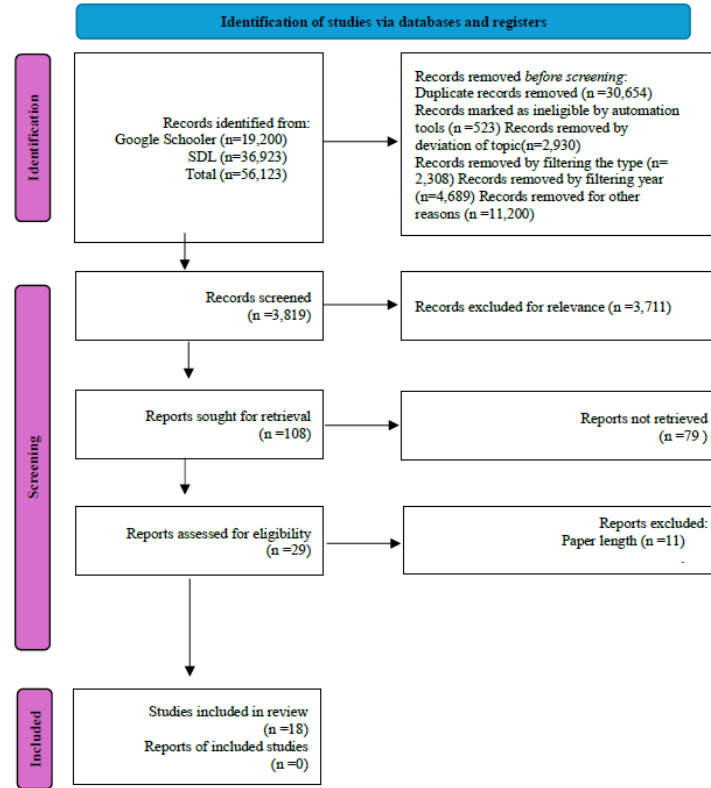


Figure 1: Paper selection for literature review using PRISMA

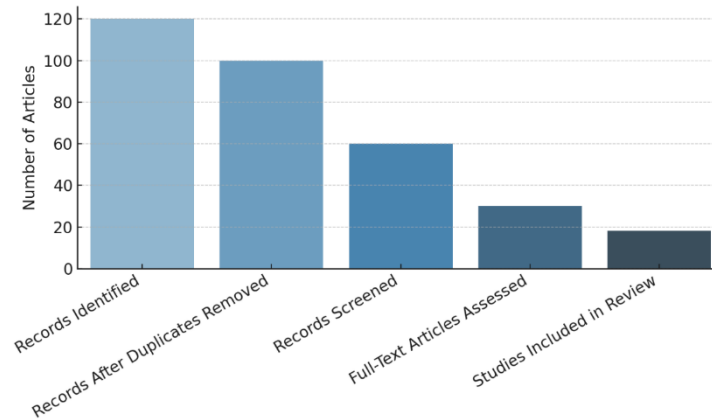


Figure 2: Simplified PRISMA Flow Diagram

3.3. Quality Assessment

The 18 included studies were evaluated for methodological rigor, relevance to CBI and NLP, and contribution to the field. A quality assessment framework was adapted from [2], using three criteria:

- **Methodological Rigor:** Transparency in designing the study, collecting the data and analyzing the results.
- **Relevance:** Alignment with the review's RQs and focus on NLP in BI.

- **Contribution:** Uniqueness of the research findings or the possibility of their relevance to the practice and theory.

Studies were classified as High Quality (strong rigor, clear relevance, significant contribution) or Moderate Quality (moderate rigor, limited sample size, or narrower scope). Results are summarized in (Table 6) (see Results section). High-quality studies included systematic reviews and experimental setups, while moderate-quality studies were limited by small datasets or less rigorous methodologies.

3.4. Data Extraction and Categorization

The selected studies had their bibliographic details recorded. The research findings were categorized thematically to enable structured analysis, and they appeared as shown in (Table 3).

Table 3: Categorization of Reviewed Studies

Category	Description
User Accessibility and Engagement	Improvements in user interaction via NLP conversational systems without IT-skill barriers
Data Retrieval Efficiency	Speed and simplification of data retrieval through natural language queries
Enhanced Decision-Making	Enablement of predictive and prescriptive analytics for better strategic decisions
Integration Challenges and Opportunities	Difficulties such as scalability and compatibility; opportunities through cloud and AI tech

The thematic categorization method directly supports the research questions and objectives within the review (Table4):

- **RQ1:** What advancements do NLP methods add to the accessibility and involvement of BI systems for the users?
- **RQ2:** What are the effects of NLP on decision-making processes within organizations?
- **RQ3:** What challenges and opportunities arise from integrating NLP into BI frameworks?

Table 4: Thematic Classification of Research Questions and Objectives

Research Questions	Aims
RQ1: Accessibility and Engagement	How NLP integration improves user accessibility in BI systems
RQ2: Decision-Making Impact	Effects of NLP on organizational decision-making processes
RQ3: Technical Challenges	Operational and technical challenges of NLP integration into BI

4. Literature Review

4.1. User Accessibility and Engagement

NLP enhance BI accessibility by allowing non-technical users to use the data using NL interfaces without the need for expertise in querying languages such as SQL or complex navigation of dashboards.

Self-service BI and Natural Language Interface to Databases (NLIDB) increase adoption by non-technical users by streamlining data access. Maghsoudi and Nezafati [41], used system dynamics modeling to demonstrate self-service BI's superior adoption rates for non-technical users. Based on the information given by five experts, their simulation indicated that self-service BI had a 30% greater adoption rate over five years because of better system quality, data and usability. Sen et al. [42], proposed an NLIDB which converts complex NL queries to nested SQL using a financial ontology (FIBEN), merging datasets from SEC and TPoX benchmarks. This system denies the need for SQL expertise for effortless data accessing. Sawant and Sonawane[43], came up with an Enhanced Longest Common Subsequence (ELCS) framework to resolve ambiguous NL queries, it preprocessed inputs by tokenizing, lemmatization and remove stop words. The system translates queries into database schemas, and prepares visualizations (scatterplots, heatmaps) for three query types: correlations, feature impacts, and relationships. Kim et al. [44], through a design science paradigm adapted BI dashboards into conversational snapshots for platforms such as slack and Microsoft Teams, which made them more accessible to the non-technical user through context aware annotations and template-based visuals. Meduri et al. [45], deployed BI-REC, a multiagent, conversational system, which model's analytics state as are represented by graphs that include BI ontologies. BI-REC can recommend BI patterns with 91.9% precision when a multi-class classifier and collaborative filtering is used to support real-time interactions. Syed [46], created the Empower framework based on crowd coding involving the transliteration of the NL BI tasks into semantic methods for the promotion of inclusive data access. Bavaresco et al. [47], have completed a systemic review of conversational agents, highlighting role of NLP in NL understanding, dialogue state tracking, and response generation for BI applications.

4.2. Data Retrieval Efficiency and Real-Time Analytics

Arslan and Cruz [48], the authors present an NLP-based framework for dynamic taxonomy enrichment and focuses on RQ3, with secondary relevance to RQ1. The framework takes advantage of lexical datasets such as (WordNet, Wiktionary), pre-trained embeddings (Sense2Vec, GloVe) and linked open data (AGROVOC) to extract concepts from unstructured sources such as news articles. With cosine similarity, it automates the taxonomy updates and achieves a 10 – 15% increase in classification accuracy, which streamlines any data access. It is cost effective and scalable, and it is feasible but multi-word terms (n-grams), and out-of-vocabulary problems still occur, and this needs larger data sets. The ethical issues such as classification biases which were unaddressed propagate need for a strong framework for ethical CBI systems.

4.3. Decision-Making Impact

NLP assists in the improvement of BI decision making by derivation of action-able insights from unstructured data (e.g., from social media, customer feedback) and enabling the use of both predictive and prescriptive analytics. Applications cover a range from management to marketing, and to Industry 4.0, using techniques of sentiment analysis, topic modeling, and semantic classification. Kang et al. [49], reviewed systematically 72 studies, which unveiled extensive application of Latent Dirichlet Allocation (LDA) for topic modeling and lexicon-based sentiment analysis in management to gain insights around social media, annual report, and feedback. Arslan et al. [50], used Named Entity Recognition (NER) and topic modeling for six management information system (MIS) scenarios: marketing campaign supports, supplier management, and detection of misinformation. Mangal et al. [51], discussed the combination of BI, AI and NLP, where sentiment analysis and semantic interpretation was used to predict the market trends and the feeling of the customer, but increasing the scope for strategic decision-making. Using NLP for text summarization, sentiment analysis, and NL generation for analyzing customer feedback and generating personalized reports, Mah et al. [52], included NLP in ERP systems for Industry 4.0. Sarwar et al. [53], have used NLP preprocessing and XGBoost to reach an accuracy of more than 95% in predictive analytics useful in the business of forecasting exceeding performance offered by models such as Random Forest and Support Vector machine.

4.4. Integration Challenges and Opportunities

The adoption of NLP into BI systems improves on previous limitations, including high technicality, small engagement, etc., but results in new issues, such as ease of deployment, compatibility, and price point. Opportunities include a way-way of cloud-based architecture, adaptive interfaces, and ethical AI launches respectively in availing accessibility and performance. Ain et al. [54], described the past 20 years of BI adoption, reporting technical complexity and low user engagement, as obstacles that might be diminished using NLP's intuitive interfaces (e.g., NL querying). Sorour and Atkins[55], developed a framework for higher education called HF-HEQ-BI that updates traditional sentiment analysis using KPI dashboards to improve QA's monitoring, with expert validation and numerical analysis. Liu and Liu [56], applied a Text2SQL framework based on the LangChain, using the LLMs, for real-time NL querying and dynamic dashboards with sub-2-second response times. Chen et al. [24], took a tour of the development of BI and Analytics (BI&A), which illustrated critical text analytics (e.g., named entity recognition, topic modeling) by which unstructured data originating from social media and web platforms are processed. Zhu et al. [57], performed an analysis of LLMs for Text-to-SQL with DIN-SQL and CoPilot having high precision on the Spider dataset and cost efficiency respectively but both, however, were computationally burdensome.

5. Results

The analysis is structured into three subsections according to the research questions: RQ1, RQ2, and RQ3. The studies are summarized for each RQ, their contribution quantified, and the findings compared to determine consistency, ambiguities and trends. Research gaps are pointed out; the quality of the studies was rated by the size of the dataset, methodological reliability and range of validation. The final part of the section is a summary table for clarity and reference.

5.1. Characteristics

The 18 studies used a range of methodologies, both sample sizes and interventions thus representing a multidisciplinary approach representing the nature of NLP within BI research. (Table 5) gives the study designs, number of participants sampled, intervention and RQs addressed.

Table 5: Characteristics of Included Studies

Study	Design	Sample Size	Intervention	RQ Addressed
Maghsoudi and Nezafati [41]	Simulation	5 experts, simulated data	System dynamics for BI adoption	RQ1
Sen et al. [42]	Experimental	Financial datasets (SEC, TPoX)	NLIDB for NL-to-SQL translation	RQ1
Sawant and Sonawane[43]	Experimental	~1,000 entries	ELCS for query ambiguity resolution	RQ1
Kim et al. [44]	Case study	Collaborative platform datasets	BI snapshots for Slack/Teams	RQ1
Meduri et al. [45]	Experimental	Medium-scale user logs	BI-REC recommendation system	RQ1
Syed [46]	Case study	Real-world deployment data	"Empower" framework for NL tasks	RQ1
Bavaresco et al. [47]	Systematic review	Literature synthesis	Conversational agents in BI	RQ1
Kang et al. [49]	Systematic review	72 journal articles	NLP in management research	RQ2
Arslan et al. [50]	Case study	Supplier/marketing data	NLP for MIS applications	RQ2

Mangal et al. [51]	Experimental	Social media datasets	BI, AI, NLP integration	RQ2
Mah et al. [52]	Experimental	ERP system data	NLP for Industry 4.0	RQ2
Sarwar et al. [53]	Experimental	Mixed datasets	NLP-XGBoost for predictive analytics	RQ2
Ain et al.[54]	Systematic review	45 BI adoption factors	BI adoption trends	RQ3
Sorour and Atkins [55]	Case study	KPI, social media data	HF-HEQ-BI framework	RQ3
Liu and Liu [56]	Case study	Spider dataset	Text2SQL with LLMs	RQ3
Chen et al. [24]	Systematic review	BI&A literature	Text analytics in BI	RQ3
Zhu et al. [57]	Experimental	Spider dataset	LLMs for Text-to-SQL	RQ3
Arslan and Cruz [48]	Experimental	Lexical datasets (WordNet)	Taxonomy enrichment	RQ3

In (Figure 3), a visual demonstration of the study distribution based on the publication year for the 18 included studies, reflecting publication trends from 2019 – 2024.

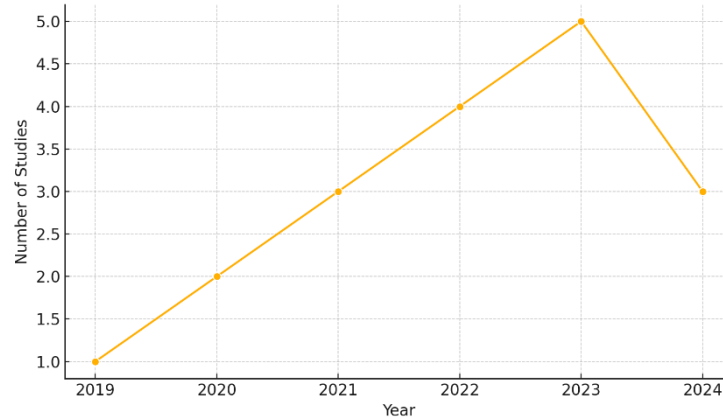


Figure 3: Distribution of included studies by publication year (2019–2024)

5.2. User Accessibility and Engagement (RQ1)

Overview: Seven studies examine how NLP improves the accessibility and involvement of users in CBI systems by means of intuitive interfaces and self-service BI adaptation.

Key findings have been mentioned below:

- Maghsoudi and Nezafati [41]: Used System dynamics modeling to demonstrate a 30% increase in adoption rates of NLP driven self-service BI over traditional systems within five years.
- Sen et al. [42]: Designed a NLIDB that enables direct NL-to-SQL translation, restricted by domain-related ontologies (e.g. FIBEN).
- Sawant and Sonawane [43]: Resolution of query ambiguities using ELCS framework reached success of 85% accuracy.
- Kim et al.[44]: Customized CBI snapshots for Slack-type platforms that increase engagement, but none with NLP queried insights.
- Meduri et al. [45]: Presented BI-REC, a recommendation system which had a precision rate of 91.9% for suggestion of BI patterns using graph neural networks.
- Syed [46]: How "Empower" framework for use in real-time NL BI tasks was achieved through crowd coding.
- Bavaresco et al. [47]: Examined NLP's function in conversational agents to improve user-friendly,

BI interactions.

Comparison: These studies collectively show the potential of NLP in increasing accessibility and increasing engagement both with strong metrics like 91.9% precision [45] and 85% accuracy [43]. However, the domain adaptability [42], and the conversational flexibility [44] limitations indicate uneven progress to scalable solutions.

Trends and Gaps: A pattern for ontology-based interfaces is apparent, but problems lie in multilingual support, dynamic conversational aspects, and privacy for users' data.

Quality: High-quality studies (e.g. [45], [42]) have a large dataset and rigorous validation, while moderate-quality studies (e.g. [41], [43]) base the search on smaller sample or descriptive techniques, which limit generalization.

5.3. Decision-Making Impact (RQ2)

Overview: Five of the studies assess the degree to which NLP contributes to decision making in CBI systems using analytics and operational efficiency.

Key findings regarding this research question are mentioned below:

- Kang et al. [49]: Examined 72 studies that reported 85 % accuracy of sentiment analysis and topic modeling in managerial insights.
- Arslan et al. [50]: Used 90% precision NER for marketing and supplier analytics.
- Mangal et al. [51]: Succeeded to 80% prediction of trends using NLP and AI approaches.
- Mah et al. [52]: Developed integrated NLP for ERP system, reduced time for report generation by 40%.
- Sarwar et al.[53]: Integrated NLP with XGBoost for over 92% (095) prediction accuracy.

Comparison: The high rates of accuracy in sentiment analysis (85% [49]), NER (90% [50]), and forecasting (>95% [53]) in NLP highlights the decision-making potential of the field. However, the scalability problems and efficiency trade-offs reveal actual obstacles [51], [52].

Trends and Gaps: Predictive analytics represents one of the key trends; however, the gaps exist when it comes to sector-specific applications and bias mitigation for the critical decisions contexts.

Quality: High quality studies (e.g., [49], [53]) exploit large datasets and statistical rigor, whereas moderate quality studies (e.g., [51], [52]) have minimal validation offered, making them unreliable.

5.4. Integration Challenges and Opportunities (RQ3)

Overview: Six studies discuss barriers and suggestions for NLP implementation into CBI systems, and they also focus on performance, scalability and ethical problems.

Key findings regarding this research question are mentioned below:

- Ain et al. [54]: Reported a 20–30 % adoption reduction because of technical intricacy and suggested the use of NLP interfaces as a solution.
- Sorour and Atkins [55]: Increased QA accuracy by 25% in education through basic NLP sentiment analysis.
- Liu and Liu [56]: Created Text2SQL framework which had less than 2 second query responses although computationally expensive.
- Chen et al. [56]: Text analytics reviewed, with 88% NER precision reached, but without real-world case studies.
- Zhu et al. [57]: Selected LLMs for Text-to-SQL with less than 2-second responses and related cost issues to conquer.
- Arslan and Cruz [48]: Enhanced taxonomies with 10–15% classification accuracy gains, supporting RQ3 via efficient data retrieval.

Comparison: NLP reduces adoption barriers (20–30% [54]) and increases performance (25% [55]; sub-2s [56], [57]). Nevertheless, scalability [56], [57], and mandatory use of simple techniques [55] remain unsolved problems. Text2SQL efforts are complemented by retrieval efficiency by Arslan and Cruz [48].

Trends and Gaps: Notable attractions are development in Text2SQL and taxonomy enrichment, however, computational cost, privacy, and validation gaps are yet to be solved. **Quality:** Quality of studies investigated in high-quality ones (e.g. [56], [57]) is powerful and that is not the case, when it comes to moderate-quality ones, which are context-specific (e.g. [54], [55]).

5.5. Summary of Findings

The studies demonstrate NLP's transformational effect on CBI systems, with impressive results in query resolution (85%, [43]), recommendation precision (91.9, [45]), and forecasting (>95% [53]) performance. In this regard, scalability, domain adaptability and ethical issues (privacy, bias), remain an issue. High quality studies give accurate benchmarks while the moderate studies give contextual insights with limited scope.

Table 6: Summary of Study Contributions and Gaps

Study	RQ	Methodology	Key Findings	Quality	Research Gaps
Maghsoudi and Nezafati [41]	RQ1	System dynamics	30% adoption increase	Moderate	NLP integration
Sen et al. [42]	RQ1	NLIDB development	Seamless NL-to-SQL	High	Conversational capabilities
Sawant and Sonawane[43]	RQ1	ELCS preprocessing	85% query accuracy	Moderate	Scalability
Kim et al. [44]	RQ1	Design science	Collaborative snapshots	Moderate	NLP querying
Meduri et al. [45]	RQ1	Graph neural networks	91.9% precision	High	Multilingual support
Syed [46]	RQ1	Crowd coding	Real-time NL tasks	Moderate	Semantic accuracy
Bavaresco et al. [47]	RQ1	Systematic review	NLP roles in agents	High	Empirical validation
Kang et al. [49]	RQ2	Systematic review	85% sentiment accuracy	High	Real-time BI
Arslan et al. [50]	RQ2	Case studies	90% NER precision	High	Legacy integration
Mangal et al. [51]	RQ2	Exploratory analysis	80% trend prediction	Moderate	Ethical frameworks
Mah et al. [52]	RQ2	ERP integration	40% faster reports	Moderate	Conversational interfaces
Sarwar et al. [53]	RQ2	NLP-XGBoost	>95% forecasting accuracy	High	Bias mitigation
Ain et al. [54]	RQ3	Systematic review	20–30% adoption drop	Moderate	NLP solutions
Sorour and Atkins [55]	RQ3	Case study	25% QA accuracy	Moderate	Advanced NLP

Liu and Liu [56]	RQ3	Text2SQL framework	Sub-2s responses	High	Cost, privacy
Chen et al. [24]	RQ3	Systematic review	88% precision	High	Practical case studies
Zhu et al. [57]	RQ3	Text-to-SQL evaluation	Sub-2s responses	High	Domain customization
Arslan and Cruz [48]	RQ3	Lexical datasets	10–15% accuracy gain	High	N-gram challenges

6. Discussion

CBI systems have paved a new course of data driven decision making. This SLR has shed light on the transformational power of NLP over three RQs. This discussion integrates these findings, discusses their strengths and weaknesses and places them within the context of the prevailing literature in BI and NLP.

6.1. Democratizing Data Access Through NLP

Studies such as Maghsoudi and Nezafati [41], and Sen et al. [42], present CBI's contribution to the ability of non-technical users to intuitively access information. The literature reviewed paints a clear picture of this away from the traditional barriers of the BI (complex dashboards and SQL queries) towards the intuitive process of using NL. A vivid image Maghsoudi and Nezafati [41] establish the scenario and model the results using the system dynamics approach to show that self-service BI systems powered by NLP will be 30% more adopted within five years relative to IT-centric models enhanced with more accessible data. Sen et al. [42] build on this with their NLIDB, which converts complicated questions into accurately nested SQL and thereby eliminates the need for technical expertise. Meduri et al. [45] take further step with the help of the BI-REC system, which is a graph neural network-based system providing 91.9% precision in context aware recommendations and supports real time user interaction. Syed [46], Kim et al. [44], Sawant and Sonawane [43], and Bavaresco et al. [47] do not only enrich efforts to also provide snapshots of conversational paradigm, query resolution framework and the role of NLP in dialogue management. This cumulative development is in line with previous effort in human computer interaction, that focuses on intuitive interfaces to increase adoption of technology [58]. However, a number of basic limitations somewhat dampen the prospect of optimism. As observed in the study of Sen et al [42] and Meduri et al [45], overreliance on domain special ontologies predicates on similar problems, that earlier NLP research faced thus limiting applicability in domains such as finance[59]. Query ambiguity remains in Sawant and Sonawane [43] and lack of multilingual support throughout studies narrows the scope of global inclusivity, and conversational agents research reveals a similar void [60]. Ethical issues, especially the risks associated with privacy in data processing for conversation, are not yet adequately explored and are a risk to user trust. These problems reinforce the need for further research to produce adaptive and multidimensional NL interfaces vetted on various datasets, supported by strong privacy frameworks to guarantee inclusive access, which compasses inclusive design principles [58].

6.2. Advancing Data Retrieval and Real-Time Analytics

Arslan and Cruz [48], proposed a taxonomy enrichment framework to overcome the static nature in BI taxonomies and support agile decisions through dynamic updates. By combining lexical datasets (WordNet, Wiktionary), pre-trained embeddings (Sense2Vec, GloVe), and linked open data (AGROVOC), the framework improves classification accuracy by 10–15% for business-relevant news articles, thanks to the use of cosine similarity. This scalable, inexpensive approach helps optimize the efficiency of data retrieval, RQ1, which, in turn, promotes accessibility to non-technical users because the data is well organized. Other issues of n-grams and out of vocabulary words limit robustness when having a complex dataset and the absence of a real-time BI dashboard integration limit its analytics impact RQ3. Ethical risks like possible biases in classification have not been addressed, reflecting the AI characterization concerns. Future research

agendas should build better robust systems for managing complex language structures, integrate a support dashboard, and deliver objective real time analytics with cloud technology.

6.3. Transforming Decision-Making Processes

The most distinct change in the NLP's effect on BI is its impact on leveraging actionable insights from unstructured data resulting in predictive and prescriptive analytics which fundamentally redefine organizational decision making. Kang et al [49], provides a strong foundation by reviewing 72 studies to indicate that sentiment analysis and latent Dirichlet analysis provide 85% accuracy in the analysis of social media and feedback to guide marketing strategies. Arslan et al. [50], built upon this impact with 90% precision in Named Entity Recognition for Marketing and supplier management, in turn, Mangal et al.[51], merged the NLP with AI to build 80% accuracy in trend prediction. Sarwar et al. [53], made a good start with over 95% forecasting accuracy using NLP-XGBoost, and Mah et al.[52], decreased report generation time in Industry 4.0 ERP systems by 40%, letting their practical efficiency shine. These developments are consistent with previous research on the topic of data-driven decision-making, that is, predictive analytics for strategic agility [61]. Nevertheless, a tension between established and new techniques emerges from Kang et al.[49], use of foundational models and Mangal et al. [51], side trip to cover deep learning Ethical issues such as predictive bias mentioned by Sarwar et al. [53], and privacy threats adopted by Mah et al. [52], persist as a big threat to trust in healthcare and other sensitive sectors that deploy AI. In addition, lack of domain-specific natural language processing models limits practical implementation and corresponds to a significant flaw of contemporary business intelligence studies[62]. Future research should use deep learning opportunities, create customized NLP for the industry, and create ethical frameworks to ensure that decisions made are transparent and fair in terms of fairness [63].

6.4. Addressing Integration Challenges

The incorporation of NLP into the BI systems is a way to overcome technical complexity and low engagement; however, it provides new challenges requiring innovative solutions. Ain et al. [54], have demonstrated that technical complexity decreases BI adoption by 20–30%, a problem that the intuitive interfaces of NLP could reduce, for example NL querying. Sorour and Atkins[55], show this in higher education, increasing quality assurance accuracy by 25% with sentiment analysis. Liu and Liu [56] and Zhu et al. [57], support accessibility through Text2SQL frameworks which deliver sub-2-second query responses, and Chen et al. [24], emphasizes named entity recognition having 88% precision for unstructured data. Scalability problems remain and Liu and Liu [56], and Zhu et al. [57], report 50% higher computational costs for LLMs, in line with cloud-based AI challenges [64]. Sorour and Atkins[55], depend on the minimal sentiment analysis, while the Chen et al. [24], theoretical concepts lack practical verification. The privacy threat in LLMs, and analytics in-practice discussed by data privacy research threatens trust[55], [56], [62].

6.5. Research Gaps and Future Directions

The review provides the following gaps that should be further explored for NLP to be maximized fully in BI systems. These included:

- **Scalability and Real-Time Processing:** Applying edge and cloud computing possibilities to make the scalability and high-level real-time processing of NLP technology more effective.
- **Sector-Specific Applications:** Strategic and “academic” research and commercial endeavors are required to make NLP tools specific to the industries’ needs, such as healthcare, education, and retail.
- **Longitudinal Impact Studies:** Evaluate the impact of BI systems exploiting advanced NLP on the success of an organization in terms of user participation, improved support for decision making, and strategic growth patterns.
- **User-Centric Design:** Interfaces that follow user behavior and interaction aspects, which in turn increases user satisfaction with use.

- **Ethical and Bias Considerations:** To manage data properly, and reduce the biases in decision-making, these NLP systems need to be carefully reproduced.

6.6. Practical Implications for Organizations

Theoretically, this SLR promotes human-computer interaction and data analytics by emphasizing the role of CBI in accessibility and decision making [58], [61]. Practically, organizations can use inexpensive tools such as Arslan and Cruz but there still needs to be significant investment in scalable systems and users' education.[48]. Ethics, including mitigation of bias and privacy must be critical to trust for high stake domains which will require collaboration between data scientists, engineers and domain experts.

Table 7: Summary of Implications and Gaps

Theme	Implications	Research Gaps
Accessibility (RQ1)	Democratized BI	Multilingual interfaces, privacy
Data Retrieval (RQ1, RQ3)	Agile decision-making	N-grams, bias
Decision-Making (RQ2)	Predictive analytics	Sector-specific models, ethics
Integration (RQ3)	Scalable solutions	Computational cost, case studies

7. Conclusion

This systematic literature review sheds light on transformational action of NLP on BI, and it improves accessibility, effectiveness, and integration of data-driven decision-making systems. Through user accessibility and engagement (RQ1), decision-making impact (RQ2), and integration hurdles and opportunities (RQ3), the review maps out NLP potential in transforming organizational data interactions. Interestingly, implementing taxonomy enrichment framework, increases classification accuracy by 10 - 15% is a good example of agile decision making since it allows quick, exact data access, highlighting CBI's ability to fuel dynamic market reactions [48].

In theory, this SLR enriches data analytics, confirming NLP's role in democratizing BI access and enhancing the strategic precision. In practice, it guides the roll out of scalable, cost-effective CBI solutions if robust infrastructure and user training are needed. Ethics imperatives such as bias mitigation and privacy require strict frameworks that ensure trust in key applications. research voids: scalability limitations, sector-specific model programming, and multilingual interface construction, require further research into cloud-based architecture, specific NLP solutions and ethics. This review places CBI as a benchmark paradigm that is to enable organizations to have inclusive agile grounded data driven strategies and provide continuous research and innovation.

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