Machines and Algorithms
http://www.knovell.org/mna

*Review Article*

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

**Maryam Almusallam [1,*], Sajid Iqbal[1]**

[1]Department of Information Systems, College of Computer Science and Information Technology, King Faisal University, Al Hofuf, 31982, Saudi Arabia

[*]Corresponding Author: Maryam Almusallam. Email: maryamabdulaziz.m@gmail.com

Received: 02 December 2024; Revised: 01 January 2025; Accepted: 04 February 2025; Published: 20 March 2025

AID: 004-01-000046

**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).

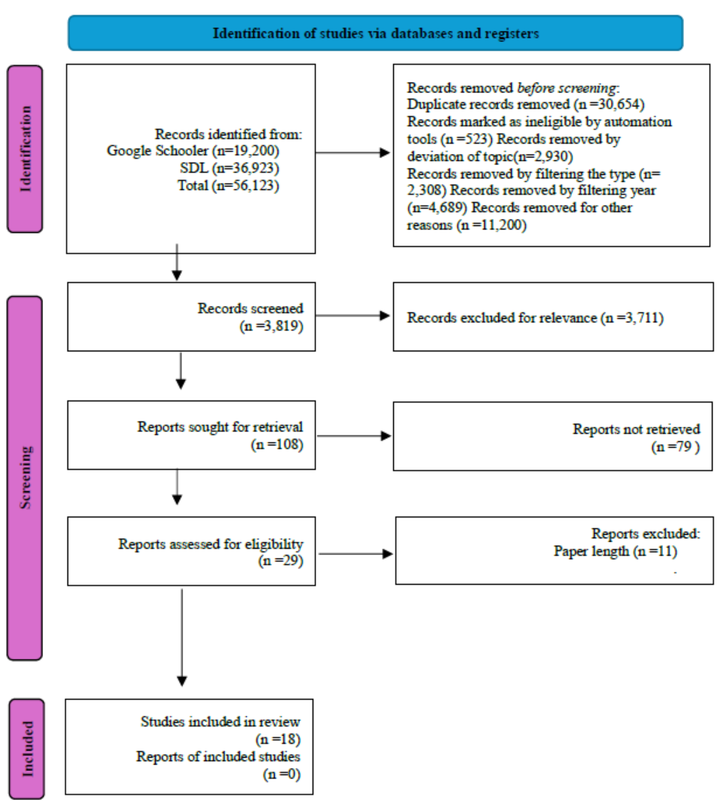


**Figure 1:** Paper selection for literature review using PRISMA

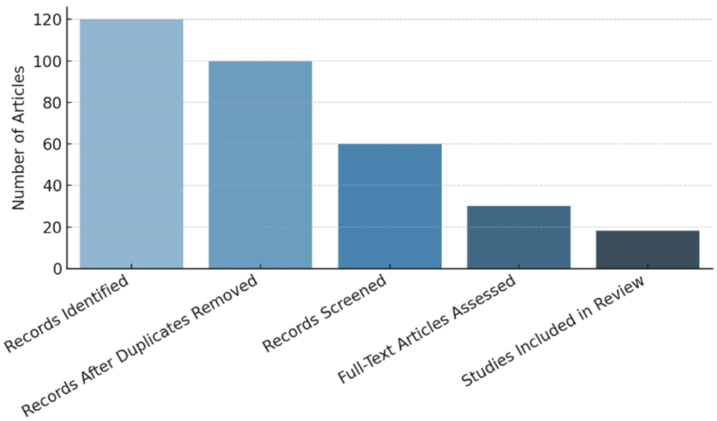


**Figure 2:** Simplified PRISMA Flow Diagram

### *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.

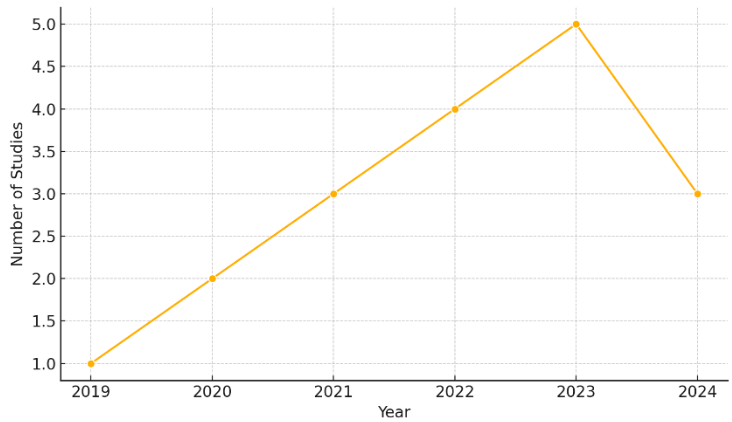


**Figure 3:** Distribution of included studies by publication year (2019–2024)

### *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% NER 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.

**Funding Statement:** No external funding was received for this research.

**Conflicts of Interest:** The authors declare that they have no conflict of interest.

**Data Availability:** This study is a literature review analysis and do not utilize any dataset for analysis.

## References

[1] Mayer, Duncan J., and Robert L. Fischer. "Exploring data use in nonprofit organizations." *Evaluation and Program Planning* 97 (2023): 102197.

[2] Niu, Yanfang, Limeng Ying, Jie Yang, Mengqi Bao, and C. B. Sivaparthipan. "Organizational business intelligence and decision making using big data analytics." *Information Processing & Management* 58, no. 6 (2021): 102725.

[3] Adewusi, Adebunmi Okechukwu, Ugochukwu Ikechukwu Okoli, Ejuma Adaga, Temidayo Olorunsogo, Onyeka Franca Asuzu, and Donald Obinna Daraojimba. "Business intelligence in the era of big data: a review of analytical tools and competitive advantage." *Computer Science & IT Research Journal* 5, no. 2 (2024): 415-431.

[4] Aljawarneh, Nader Mohammad. "The mediating role of organization agility between business intelligence & innovative performance." *Journal of Statistics Applications & Probability* 13, no. 3 (2024): 929-938.

[5] Jiménez-Partearroyo, Montserrat, and Ana Medina-López. "Leveraging business intelligence systems for enhanced corporate competitiveness: Strategy and evolution." *Systems* 12, no. 3 (2024): 94.

[6] Banisharif, Mahdi, Arman Mazloumzadeh, Mohammadreza Sharbaf, and Bahman Zamani. "Automatic generation of business intelligence chatbot for organizations." In *2022 27th International Computer Conference, Computer Society of Iran (CSICC)*, pp. 1-5. IEEE, 2022.

[7] Williams, Randy A., Gazi Murat Duman, Elif Kongar, and Dan Tenney. "Understanding Business Intelligence Implementation Failure from Technology, Organization, and Process Perspectives." *IEEE Engineering Management Review* 52, no. 1 (2023): 151-176.

[8] Garn, Wolfgang. *Data Analytics for Business: Ai-Ml-pbi-sql-r*. Routledge, 2024.

[9] Ranjbarfard, Mina, and Zeynab Hatami. "Critical success factors for implementing business intelligence projects (a BI implementation methodology perspective)." *Interdisciplinary Journal of Information, Knowledge, and Management* 15 (2020): 175-202.

[10] Golestanizadeh, Mahboobeh, Hadi Sarvari, Amirhossein Parishani, Nelson Akindele, and David J. Edwards. "Probing the Effect of Business Intelligence on the Performance of Construction Projects Through the Mediating Variable of Project Quality Management." *Buildings* 15, no. 4 (2025): 621.

[11] Moitas, João, João Albuquerque, and Rúben Mano. "Business Intelligence Implementation and its Impact on Decision-making." In *2023 18th Iberian Conference on Information Systems and Technologies (CISTI)*, pp. 1-7. IEEE, 2023.

[12] Hosen, Mohammed Shahadat, Raisul Islam, Zain Naeem, E. O. Folorunso, Thai Son Chu, M. A. Al Mamun, and N. O. Orunbon. "Data-driven decision making: Advanced database systems for business intelligence." *Nanotechnology Perceptions* 20, no. 3 (2024): 687-704.

[13] Alparslan, Adem. "The Role of Accuracy and Validation Effectiveness in Conversational Business Analytics." *IEEE Access* (2025).

[14] Vashisht, Vipul, and Pankaj Dharia. "Integrating chatbot application with qlik sense business intelligence (BI) tool using natural language processing (NLP)." In *Micro-Electronics and Telecommunication Engineering: Proceedings of 3rd ICMETE 2019*, pp. 683-692. Singapore: Springer Singapore, 2020.

[15] Goar, Vishal, Nagendra Singh Yadav, and Pallavi Singh Yadav. "Conversational AI for natural language processing: An review of ChatGPT." *International Journal on Recent and Innovation Trends in Computing and Communication* 11, no. 3s (2023): 109-17.

[16] Quamar, Abdul, Fatma Özcan, Dorian Miller, Robert J. Moore, Rebecca Niehus, and Jeffrey Kreulen. "Conversational BI: An ontology-driven conversation system for business intelligence applications." *Proceedings of the VLDB Endowment* 13, no. 12 (2020): 3369-3381.

[17] Arjunan, Tamilselvan. "Building business intelligence data extractor using nlp and python." *International Journal for Research in Applied Science and Engineering Technology* 10, no. 10 (2022): 23-28.

[18] Michalczyk, Sven, Mario Nadj, Darius Azarfar, Alexander Maedche, and Christoph Gröger. "A state-of-the-art overview and future research avenues of self-service business intelligence and analytics." (2020).

[19] Casciani, Angelo, Mario L. Bernardi, Marta Cimitile, and Andrea Marrella. "Conversational systems for AI-augmented business process management." In *International conference on research challenges in information science*, pp. 183-200. Cham: Springer Nature Switzerland, 2024.

[20] Jain, Aditi. "AI-Powered Business Intelligence Dashboards: A Cross-Sector Analysis of Transformative Impact and Future Directions." (2024).

[21] Awan, Usama, Saqib Shamim, Zaheer Khan, Najam Ul Zia, Syed Muhammad Shariq, and Muhammad Naveed Khan. "Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance." *Technological Forecasting and Social Change* 168 (2021): 120766.

[22] Fotache, Marin. "Data Processing Languages for Business Intelligence. SQL vs. R." *Informatica Economica* 20, no. 1 (2016).

[23] Spahn, Michael, Joachim Kleb, Stephan Grimm, and Stefan Scheidl. "Supporting business intelligence by providing ontology-based end-user information self-service." In *Proceedings of the First international Workshop on ontology-Supported Business intelligence*, pp. 1-12. 2008.

[24] Chen, Hsinchun, Roger HL Chiang, and Veda C. Storey. "Business intelligence and analytics: From big data to big impact." *MIS quarterly* (2012): 1165-1188.

[25] Chaudhuri, Surajit, Umeshwar Dayal, and Vivek Narasayya. "An overview of business intelligence technology." *Communications of the ACM* 54, no. 8 (2011): 88-98.

[26] Diván, Mario José. "Data-driven decision making." In *2017 international conference on Infocom technologies and unmanned systems (trends and future directions)(ICTUS)*, pp. 50-56. IEEE, 2017.

[27] Uddin, Md Kazi Shahab. "A review of utilizing natural language processing and AI for advanced data visualization in real-time analytics." *Global Mainstream Journal* 1, no. 4 (2024): 10-62304.

[28] Torfi, Amirsina, Rouzbeh A. Shirvani, Yaser Keneshloo, Nader Tavaf, and Edward A. Fox. "Natural language processing advancements by deep learning: A survey." *arXiv preprint arXiv:2003.01200* (2020)

[29] Rane, Nitin, Mallikarjuna Paramesha, Saurabh Choudhary, and Jayesh Rane. "Business intelligence through artificial intelligence: A review." *Available at SSRN 4831916* (2024).

[30] Kokab, Sayyida Tabinda, Sohail Asghar, and Shehneela Naz. "Transformer-based deep learning models for the sentiment analysis of social media data." *Array* 14 (2022): 100157.

[31] Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "Bert: Pre-training of deep bidirectional transformers for language understanding." In *Proceedings of the 2019 conference of the North American chapter*

*of the association for computational linguistics: human language technologies, volume 1 (long and short papers)*, pp. 4171-4186. 2019.

[32] Brown, Tom, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D. Kaplan, Prafulla Dhariwal, Arvind Neelakantan et al. "Language models are few-shot learners." *Advances in neural information processing systems* 33 (2020): 1877-1901.

[33] Alonso, Miguel A., Carlos Gómez-Rodríguez, and Jesús Vilares. "On the use of parsing for named entity recognition." *Applied sciences* 11, no. 3 (2021): 1090.

[34] Zheng, Yang, Yongkang Liu, and John HL Hansen. "Intent detection and semantic parsing for navigation dialogue language processing." In *2017 IEEE 20th international conference on intelligent transportation systems (ITSC)*, pp. 1-6. IEEE, 2017.

[35] Affolter, Katrin, Kurt Stockinger, and Abraham Bernstein. "A comparative survey of recent natural language interfaces for databases." *The VLDB Journal* 28, no. 5 (2019): 793-819.

[36] Liao, Q. Vera, Daniel Gruen, and Sarah Miller. "Questioning the AI: informing design practices for explainable AI user experiences." In *Proceedings of the 2020 CHI conference on human factors in computing systems*, pp. 1-15. 2020.

[37] Abdul-Kader, Sameera A., and John C. Woods. "Survey on chatbot design techniques in speech conversation systems." *International Journal of Advanced Computer Science and Applications* 6, no. 7 (2015).

[38] Núñez-Molina, Carlos, Pablo Mesejo, and Juan Fernández-Olivares. "A review of symbolic, subsymbolic and hybrid methods for sequential decision making." *ACM Computing Surveys* 56, no. 11 (2024): 1-36.

[39] Goertzel, Ben. "Perception processing for general intelligence: Bridging the symbolic/subsymbolic gap." In *International Conference on Artificial General Intelligence*, pp. 79-88. Berlin, Heidelberg: Springer Berlin Heidelberg, 2012.

[40] Rethlefsen, Melissa L., and Matthew J. Page. "PRISMA 2020 and PRISMA-S: common questions on tracking records and the flow diagram." *Journal of the Medical Library Association: JMLA* 110, no. 2 (2022): 253.

[41] Maghsoudi, Mehrdad, and Navid Nezafati. "Navigating the acceptance of implementing business intelligence in organizations: A system dynamics approach." *Telematics and Informatics Reports* 11 (2023): 100070.

[42] Sen, Jaydeep, Fatma Ozcan, Abdul Quamar, Greg Stager, Ashish Mittal, Manasa Jammi, Chuan Lei, Diptikalyan Saha, and Karthik Sankaranarayanan. "Natural language querying of complex business intelligence queries." In *Proceedings of the 2019 International Conference on Management of Data*, pp. 1997-2000. 2019.

[43] Sawant, Pradnya, and Kavita Sonawane. "NLP-based smart decision making for business and academics." *Natural Language Processing Journal* 8 (2024): 100090.

[44] Kim, Hyeok, Arjun Srinivasan, and Matthew Brehmer. "Bringing Data into the Conversation: Adapting Content from Business Intelligence Dashboards for Threaded Collaboration Platforms." In *2024 IEEE Visualization and Visual Analytics (VIS)*, pp. 81-85. IEEE, 2024.

[45] Meduri, Venkata Vamsikrishna, Abdul Quamar, Chuan Lei, Vasilis Efthymiou, and Fatma Ozcan. "BI-REC: guided data analysis for conversational business intelligence." *arXiv preprint arXiv:2105.00467* (2021).

[46] Syed, Shakir. "Breaking Barriers: Leveraging Natural Language Processing In Self-Service Bi For Non-Technical Users." *Available at SSRN 5032632* (2022).

[47] Bavaresco, Rodrigo, Diórgenes Silveira, Eduardo Reis, Jorge Barbosa, Rodrigo Righi, Cristiano Costa, Rodolfo Antunes et al. "Conversational agents in business: A systematic literature review and future research directions." *Computer Science Review* 36 (2020): 100239.

[48] Arslan, Muhammad, and Christophe Cruz. "Semantic Enrichment of Taxonomy for BI Applications using Multifaceted data sources through NLP techniques." *Procedia Computer Science* 207 (2022): 2424-2433.

[49] Kang, Yue, Zhao Cai, Chee-Wee Tan, Qian Huang, and Hefu Liu. "Natural language processing (NLP) in management research: A literature review." *Journal of Management Analytics* 7, no. 2 (2020): 139-172.

[50] Arslan, Muhammad, Zainab Riaz, and Christophe Cruz. "Revolutionizing management information systems with natural language processing for digital transformation." *Procedia Computer Science* 225 (2023): 2835-2844.

[51] Mangal, Umesh, Sandeep Mogha, and Sumit Malik. "Data-Driven Decision Making: Maximizing Insights Through Business Intelligence, Artificial Intelligence and Big Data Analytics." In *2024 International Conference on Advances in Computing Research on Science Engineering and Technology (ACROSET)*, pp. 1-7. IEEE, 2024.

[52] Mah, Pascal Muam, Iwona Skalna, and John Muzam. "Natural language processing and artificial intelligence for enterprise management in the era of industry 4.0." *Applied Sciences* 12, no. 18 (2022): 9207.

[53] Sarwar, Uzma, Narinder Kumar Bhasin, Dibyahash Bordoloi, Sunil Kadyan, S. Kezia, and S. Muthuperumal. "Revolutionizing Business Intelligence with AI Insights and Strategies." In *2024 8th International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*, pp. 1883-1889. IEEE, 2024.

[54] Ain, NoorUl, Giovanni Vaia, William H. DeLone, and Mehwish Waheed. "Two decades of research on business intelligence system adoption, utilization and success–A systematic literature review." *Decision Support Systems* 125 (2019): 113113.

[55] Sorour, Ali, and Anthony S. Atkins. "Big data challenge for monitoring quality in higher education institutions using business intelligence dashboards." *Journal of Electronic Science and Technology* 22, no. 1 (2024): 100233.

[56] Liu, Jinxia, and Pei Liu. "Research on the application of artificial intelligence technology in traditional business intelligence systems." In *2024 4th International Symposium on Computer Technology and Information Science (ISCTIS)*, pp. 186-190. IEEE, 2024.

[57] Zhu, Jerry, Saad Ahmed Bazaz, Srimonti Dutta, Bhavaraju Anuraag, Imran Haider, and Srijita Bandopadhyay. "Talk to your data: Enhancing business intelligence and inventory management with llm-driven semantic parsing and text-to-sql for database querying." In *2023 4th international conference on data analytics for business and industry (ICDABI)*, pp. 321-325. IEEE, 2023.

[58] Nielsen, Jakob. *Usability engineering*. Morgan Kaufmann, 1994.

[59] McDaniel, Melinda, and Veda C. Storey. "Evaluating domain ontologies: clarification, classification, and challenges." *ACM Computing Surveys (CSUR)* 52, no. 4 (2019): 1-44.

[60] Xu, Anbang, Zhe Liu, Yufan Guo, Vibha Sinha, and Rama Akkiraju. "A new chatbot for customer service on social media." In *Proceedings of the 2017 CHI conference on human factors in computing systems*, pp. 3506-3510. 2017.

[61] Xu, Anbang, Zhe Liu, Yufan Guo, Vibha Sinha, and Rama Akkiraju. "A new chatbot for customer service on social media." In *Proceedings of the 2017 CHI conference on human factors in computing systems*, pp. 3506-3510. 2017.

[62] Modi, Tejaskumar B. "Artificial Intelligence Ethics and Fairness: A study to address bias and fairness issues in AI systems, and the ethical implications of AI applications." *Revista Review Index Journal of Multidisciplinary* 3, no. 2 (2023): 24-35.

[63] Hardt, Moritz, Eric Price, and Nati Srebro. "Equality of opportunity in supervised learning." *Advances in neural information processing systems* 29 (2016).

[64] Lee, Juhnyoung. "A view of cloud computing." *International Journal of Networked and Distributed Computing* 1, no. 1 (2013): 2-8.