Opportunities and Challenges for AI-supported Business Intelligence Systems – A Delphi Study

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Abstract

In a progressively data-driven environment, business intelligence has emerged as a crucial function fostering efficiency, competitiveness, and innovation. Thus, the growing volume of data necessitates more extensive analysis. In addition, ensuing data complexity requires increasing capacities of skilled workers. Using artificial intelligence appears promising to not only handle but utilize increasing data volume and variety. While artificial intelligence adoption offers numerous opportunities, it also presents challenges alike. The objective of our research is to identify and synthesize the opportunities and challenges associated with incorporating artificial intelligence into business intelligence systems. To this end, we conducted a structured literature review and subsequently evaluated our findings through a Delphi study with experts from practice. Our results contribute to both practice and academia regarding potentials for harnessing opportunities and mastering challenges towards the future of artificial intelligence in business intelligence systems.

Keywords: Artificial intelligence, Business intelligence, Delphi study

1. Introduction

Artificial intelligence (AI) encompasses a range of disruptive technologies that are revolutionizing many aspects of today's businesses and society (Dwivedi et al., 2023). AI-driven technologies have a significant impact on various sectors of the economy and generate enormous value creation potential (Dwivedi et al., 2023). As AI-based technologies evolve around harnessing data, there is specific potential for using AI to gather and prepare business data as part of a business intelligence (BI) strategy. The expanding data landscape amplifies the utility of AI, enabling efficient processing of massive datasets and democratizing data exploration by reducing reliance on complex queries and coding for non-technical users (Jasti, 2023; Smith et al., 2019). This development is part of a constant change within BI, which began in the 1990s with the introduction of data warehouses and is now reaching a new stage of evolution through the integration of AI (Chen et al., 2012; Prat, 2019). The implementation of AI in BI systems will change the way in which data is handled in the future (Ereth & Eckerson, 2018; Prat, 2019). As part of AI, machine learning can be used to leverage big data analysis (Bharadiya, 2023d). Intelligent software robots seem promising to automate repetitive operational processes (Mayr et al., 2023). However, there are also challenges to introducing AI in BI that must be addressed, such as lacking data quality (Zschech et al., 2019).

Despite high expectations on the impact AI will have on BI, literature on practical opportunities and challenges is scarce. Thus, our research aims to investigate not only which opportunities and challenges there are, but we also determine their likelihood of occurrence and their potential impact.

Against this background, we formulate the following research questions:

RQ1: *What opportunities and challenges arise regarding the use of artificial intelligence in business intelligence systems?*

RQ2: *What likelihood and impact do the opportunities and challenges have?*

To answer the research questions, we conducted a structured literature review and a subsequent three-

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round Delphi study with experts from practice. Our results comprise six opportunities and six challenges that have several implications for practice and theory.

The remainder of this contribution structures as follows. Section 2 covers related work on BI and the increasing intersection with AI. In Section 3, we outline the research methodology. Section 4 contains the identified opportunities and challenges. Subsequently, in Section 5, we present the results from the Delphi study. In Section 6, we discuss our results and outline implications for practice and academia. Lastly, in Section 7, we draw a conclusion and point out potential for future research.

2. Related Work

2.1. Business Intelligence

Information technology has been used to support decision-makers in business contexts for several decades (Gluchowski et al., 2008; Wixom & Watson, 2010). Various decision support systems have been developed to improve information provision and decision-making. Terminologically, BI gained popularity in the 1990s (Chen et al., 2012; Watson & Wixom, 2007). Despite its vast diffusion in practice and academia, there is no common terminological definition for BI. This is due to the broad variety of tasks and applications associated with BI. Commonly, literature categorizes definitions depending on whether their focus is rather narrow, wide, or analysis oriented. The narrow understanding of BI only includes the technological components that can be used for the preparation and presentation of data (Gluchowski et al., 2008). In contrast, the wider understanding of BI describes all applications for data storage, provision, and analysis. It covers warehousing technologies as well as extract, transform, load (ETL) technologies and all analytical applications that can be used to obtain information. The analysis-oriented understanding of BI comprises front-end applications including all model- and method-based analysis components and tools. To enable a broad range of answers to the research question, we take a wide understanding of BI as “umbrella term that is commonly used to describe the technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help users make better decisions” (Wixom & Watson, 2010, p. 16).

As all BI tasks and applications focus on the use of data, recent technological advancements led to radical changes in the field of BI (Alghamdi & Al-Baity, 2022; Prat, 2019). On the one hand, digitization entails a vast proliferation of data in various corporate contexts. For example, the use of sensor technology in production and logistics enables capturing data that were previously unobtainable (Chen et al., 2012). On the other hand, advancements in computation power enhance the use of AI algorithms for data analysis and visualization (Alghamdi & Al-Baity, 2022; Prat, 2019). Building on technological advancements, literature differentiates three generations of BI (Alghamdi & Al-Baity, 2022; Prat, 2019). Gaining popularity in the 1990s, BI 1.0 builds on relational database management systems, which record and store structured data from various legacy systems. ETL tools are used to prepare and integrate data. In addition, online analytical processing tools and simple statistical methods are used to analyze the company data. Dashboards and scorecards were used to present and visualize the processed data. BI 2.0 included web-based, unstructured data in companies’ analysis systems. This enabled organizations to capture and analyze a large amount of previously unavailable industry, product, and customer information. BI 2.0 is equipped with all the capabilities of DBMS-based BI 1.0 systems and integrates scalable techniques in the areas of text mining and web mining. Currently, BI 3.0 also can incorporate mobile and sensor-based data into business data analysis. This enables companies to perform location-based, person-centered, and contextual analyses in real-time (Chen et al., 2012). BI 3.0 includes BI systems supported by AI (Alghamdi & Al-Baity, 2022; Prat, 2019). The combination of AI and natural language processing (NLP) within BI platforms puts the focus on automation and data analysis with complex statistical models.

2.2. Artificial Intelligence for Corporate Decision-Making

The term AI was first established in the 1950s (Collins et al., 2021; Duan et al., 2019; Ertel, 2021; Russell & Norvig, 2023). In the early years, research was mainly concerned with knowledge-based systems that based on hard-coded statements in formal language, which a computer could then process automatically on the basis of logical inference rules (Bharadiya, 2023a; Brynjolfsson & Mcafee, 2017).

Three factors fueled the recent diffusion of AI in business contexts, such as BI (Brynjolfsson & Mcafee, 2017): First, advancements in storage and computation capacities enable using complex AI functionality in everyday business contexts. This is reinforced by cloud-based provision of AI capabilities in the context of AI-as-a-Service (Collins et al., 2021). Second, the improved performance and resource utilization of AI-based algorithms enables widespread use. Third, the stark increase in data availability leads to the need to leverage complex algorithms for data analysis.

The integration of AI is increasingly being used in the context of BI. This development is primarily since AI technologies enable more efficient processing and analysis of the constantly growing volumes of data, which supports both the improvement of existing processes and their automation. In this regard, natural language processing (NLP) proliferates as interface facilitating access to BI functionality for a variety of users (Bharadiya, 2023c).

NLP is situated at the intersection of computer science and linguistics. Since its emergence in the 1950s, NLP has undergone significant developments and is now widely used in improving human-machine communication, ML from language content and in tools such as translation programs, text mining in social media and chatbots. It engages with the use of various computer supported methods to learn, understand and generate human language (Hirschberg & Manning, 2015; Joshi et al., 2020; Jurafsky & Martin, 2008). In the context of BI, NLP is used to query databases. They represent natural language interfaces in the form of text-to-SQL systems. Models for translating between natural language and SQL are usually based on deep learning (DL) models (Hirschberg & Manning, 2015; Katsogiannis-Meimarakis & Koutrika, 2023). DL approaches learn based on pairs of natural language and correspondingly suitable SQL protocols (Affolter et al., 2019).

3. Research Methodology

Our research methodology consisted of three steps. First, we conducted a structured literature review to identify relevant publications (vom Brocke et al., 2015). To this end, the following search string was created: *("Artificial Intelligence" OR "Machine Learning" OR "Natural Language Processing") AND "Business Intelligence"*. The search string was used in the databases *AISeL*, *IEEE Xplore*, *Scopus*, and *Web of Science*. The databases were selected as they include renowned outlets on business analytics. The initial search resulted in 8823 publications after deduplication. The exclusion criterion used when assessing titles, abstracts, and full texts was missing relevance to answering the research question. That is, we decided to include a large range of publications that have an extensive basis to assess opportunities and challenges. After reading titles and abstracts, 160 publications were left. The engagement with full texts left 43 publications that were considered relevant for the research purpose.

In the second step, the 43 publications were analyzed to create a concept matrix (Webster & Watson, 2002). Following the research purpose, concepts had to reflect opportunities and challenges of AI in BI systems. The concept matrix was created by a single researcher. Assignment of publications to concepts was validated by a second researcher based on a random sample of 15 publications (35%). The Cohen's Kappa was 0.79 indicating substantial agreement between researchers (Landis & Koch, 1977; Regier et al., 2013). Building on the concept matrix, a structured questionnaire was created as instrument for a Delphi study with BI experts from practice (Bell et al., 2019).

Third, we conducted the Delphi study. In general, Delphi studies are systematic survey procedures conceived in the 1960s (Vorgrimler & Wübben, 2003). The core idea of Delphi studies is to obtain expert assessments on selected topics through several anonymous survey rounds (Häder, 2014). In each round, study participants are provided with aggregated, anonymized results of the previous round. The repetitive survey character and indications of aggregated results are supposed to enhance consent among experts (Vorgrimler & Wübben, 2003). There are several criteria to stop the Delphi study that are usually defined before initiation of the first round (Häder, 2014). Common examples are a level of consent among answers, a certain number of rounds or a certain number of experts assuming dropouts after each round.

To conduct the Delphi study, we acquired experts from practice, who work in corporate BI. Participant acquisition included approaching contacts from one author's work occupation in a business consultancy as well as addressing experts through social media. A series of twelve statements was presented to the participants, such as "Text-to-SQL systems translate complex natural language reporting queries accurately and error-free" or "conversational analytics and NPL enable information retrieval for users without specific technical expertise." There were 21 participants in the first round of the Delphi study. In round 2, one participant was added. Table 1 shows the participants' occupations and years of relevant experience.

Table 1: Characteristics of study participants.

Characteristics		**R1**	**R2**	**R3**
Years of relevant experience	<1	1	1	1
	1-3	11	11	10
	4-6	3	3	2
	7-10	4	4	2
	>10	2	3	3
Occupations	Consultant	11	11	8
	Data engineer/ scientist	5	5	5
	Other	5	6	5
Sum		**21**	**22**	**18**

Most participants have between one and three years of experience. Occupations can be divided in consultants, data engineers or data scientists as well as other BI-related occupations. The latter include, for example, AI product owners in the field of BI or lead BI architects. The predefined stopping criterion was three rounds complying to experts' availability. The Delphi study was conducted online. The study consisted of a brief introduction clarifying the procedure and the definition of the most important terms used in the items. Subsequently, the participants answered questions on their occupation and years of experience. The participants then were asked to rate the opportunities and challenges of AI in BI. Potentials were rated in terms of (1) their likelihood of occurrence until 2030 and (2) the impact on business practice. Challenges were rated in terms of (1) their likelihood to be overcome by 2030 and (2) the impact on business practice as soon as they are overcome.

4. Opportunities and Challenges of Using AI in BI Systems

Table 2 summarizes the opportunities and challenges identified from literature.

Table 2. Opportunities and challenges.

Opportunities (O)		
Data access	Real-time creation of reports and dashboards	O1
	Facilitated information retrieval	O2
	Text-to-SQL translation	O3
Data analytics and AI-based automation	Process automation	O4
	Increased speed of data analysis	O5
	AI-based predictions	O6
Challenges (C)		
Data quality and availability	Insufficient data quality	C1
	Natural language ambiguity	C2
	Lack of SQL protocols with corresponding text corpora in natural language	C3
Data and AI governance	Outdated corporate culture	C4
	Misclassification from inadequate training data	C5
	Changing roles and range of tasks	C6

Based on the structured literature review and concept matrix, we find that opportunities cover data access as well as data analytics and AI-based automation. The opportunities emphasize increased efficiency through advanced analytics and automation as well as improved accessibility of data within organizations. Conversely, the challenges can be subsumed to data quality and availability as well as data and AI governance.

4.1. Opportunities

Opportunity 1 (O1): Real-time creation of reports and dashboards. Recent developments in the application of AI in BI systems have led to the acceleration of key steps necessary for the creation of reports and dashboards (Prat, 2019; Yan & He, 2020). Streamlining the execution of necessary steps, intelligent assistants can leverage time advantages. For example, by combining visualization techniques with DL, they can reduce the time-consuming task of visualization creation for human users (Deng et al., 2023). Front-end BI tools use AI functionalities to recommend visualization types such as bar charts or maps based on the properties, correlations, and relationships of the selected data. This makes it possible to obtain adequate visualization suggestions as part of attribute selection (Alghamdi & Al-Baity, 2022). Furthermore, there are innovative applications that not only aim to provide suggestions for the selection of visualizations in real-time, but also strive for the complete automation of visualization reducing human effort (Deng et al., 2023; Joshi et al., 2020).

Opportunity 2 (O2): Facilitated information retrieval. In the context of BI, AI facilitates access to data and its analysis for a broad range of users, regardless of their technical expertise (Alghamdi & Al-Baity, 2022). Traditionally, retrieving information from BI systems was linked to technical hurdles, such as query languages like SQL. As a result, access to insights was usually limited to IT personnel (Katsogiannis-Meimarakis & Koutrika, 2023). The usage of NLP in BI systems allows users to query in natural language and then automatically translate to the appropriate query language so that the BI system can deliver the desired information (Joshi et al., 2020). This simplification of interaction with BI systems allows for data access to be extended not only to technically skilled users, but also to business users from different areas (Katsogiannis-Meimarakis & Koutrika, 2023; Wong et al., 2021).

Opportunity 3 (O3): Text-to-SQL translation. The implementation of NLP and text-to-SQL systems has greatly simplified the interaction between end users and BI systems. Many of the existing data query interfaces in BI systems are suitable for a limited group of users due to their reliance on specific database query languages such as SQL (Katsogiannis-Meimarakis & Koutrika, 2023; Wong et al., 2021). Simplifying this interaction point through NLP technologies would allow a broader range of users to efficiently retrieve desired information. NLP systems allow users to formulate queries in natural language, expanding access to data and analysis results (Joshi et al., 2020; Katsogiannis-Meimarakis & Koutrika, 2023). This progress in the user interface is realized through various approaches. On the one hand, there are DL-based methods for the development of text-to-SQL systems that use neural networks with encoder and decoder components to translate natural language queries into SQL statements (Joshi et al., 2020; Katsogiannis-Meimarakis & Koutrika, 2023; Wong et al., 2021). On the other hand, there are rule-based approaches that consist of NLP processors, mapping tables and a query engine. These systems use techniques such as tokenization, stop word removal, stemming and parsing to break down the query into processable components and then translate these into database elements (Francia et al., 2022; Wong et al., 2021). To function effectively, NLP systems must be able to accurately identify tables and columns in a database and recognize necessary links between data from different sources (Wong et al., 2021). Additionally, it is important that these systems not only provide accurate query results, but also offer an interactive user experience to increase user confidence. This can be achieved through features such as evaluating the reliability of system outputs, providing natural language result summaries, query autocompletion, and displaying the generated SQL query (Joshi et al., 2020).

Opportunity 4 (O4): Process automation. AI-based automation broadly affects business processes (Mayr et al., 2023). The integration of AI and specifically NLP into BI systems leads to a fundamental transformation of the entire business analysis process (Prat, 2019). Automation can be applied specifically in the data cleansing process, data exploration, and analysis as well as in predictive modeling. Data preparation and cleansing are still considered to be the most time-consuming steps within BI applications (Yan & He, 2020). In some cases, this step takes up to 80% of the entire data analysis process. Data preparation includes all steps in which raw data from various sources is converted into formats that are suitable for BI applications (Yan & He, 2020). This ongoing process, in which information is extracted from raw data, is referred to as the ETL process (Prat, 2019; Simitsis et al., 2023; Yan & He, 2020).

Opportunity 5 (O5): Increased speed of data analysis. BI systems may incorporate AI to streamline data analysis. Various forecasting techniques are used to generate intelligent suggestions within data processing. For example, single operator prediction recommends parameter configurations for a specific data processing operation based on the properties of the given input tables (Yan & He, 2020). Operator prediction forecasts the probable next operation in a data processing pipeline by exploiting latent sequential relationships between the previous operations and the input data characteristics. In addition to providing intelligent data preparation recommendations to support BI users, there is the possibility of realizing fully automated and self-managed ETL processes in the future using AI algorithms such as reinforcement learning. To this end, the various factors influencing the ETL process, such as ETL operators, configuration parameters, data flow patterns, data sources, and historical execution data, must be coded and used to train an AI model (Simitsis et al., 2023).

Opportunity 6 (O6): AI-based predictions. In addition to AI-based support for the visual creation of dashboards, recommender systems for BI applications also increase the efficiency of data exploration and analysis by automatically identifying user interests and predicting interactions (Drushku et al., 2019). A recommender system for user interests in BI applications can build on the identification and grouping of discriminative features to characterize BI interactions and learn a similarity measure based on these features. The automatic identification of user interests offers several advantages, including the recommendation of interesting data from users with similar interests and the prediction of recurring tasks, reducing the data analysis effort. Also, significant opportunities for automation and increased efficiency can be realized in predictive modeling. The use of AI makes it possible to automate the workflow for predictive models. This may include functions for model selection, hyperparameter tuning and automatic execution of the feature engineering process (Alghamdi & Al-Baity, 2022; Prat, 2019; Schmitt, 2023). As a result, AI can increase the efficiency of analytical workflows and significantly accelerate the predictive modeling (Alghamdi & Al-Baity, 2022).

4.2 Challenges

Challenge 1 (C1): Insufficient data quality. Various technical challenges have been identified in scientific research on the implementation of AI-supported BI systems (Andriole & Barsky, 2022; Cherinka et al., 2019; Figalist et al., 2020; Merhi, 2023; Nugroho & Surendro, 2019; Prat, 2019). A key challenge is the dependence of system performance on the quality of the underlying data. Insufficient data quality and inconsistent data preparation methods can impair the performance of AI applications. Standardizing data formats and integrating information from various sources in a consistent manner is crucial. Regularly validating the accuracy and timeliness of company data stored in data warehouses is equally important (Andriole & Barsky, 2022).

Challenge 2 (C2): Natural language ambiguity. One significant obstacle in enhancing BI systems using AI is the implementation of natural language processing interfaces. In this regard, research emphasizes the challenges of translating Natural Language Queries (NLQ) into SQL queries (Francia et al., 2020; Francia et al., 2022; Joshi et al., 2020; Katsogiannis-Meimarakis & Koutrika, 2023; Li et al., 2023; Sen et al., 2019; Wong et al., 2021). The difficulties include understanding the NLQ and generating correct SQL queries based on the underlying database schema. The problem of ambiguity in natural language can complicate the correct interpretation of NLQs (Francia et al., 2022; Katsogiannis-Meimarakis & Koutrika, 2023). Synonyms and homonyms constitute major challenges in this regard. Synonyms refer to two different terms with similar semantic meaning. In contrast, homonyms refer to single terms with multiple meanings.

Challenge 3 (C3): Lack of SQL protocols with corresponding text corpora in natural language. Creating correct SQL queries from natural language, especially for complex operations such as joins and subqueries, poses a significant challenge. There is a need for precise determination of relevant tokens from NL queries as well as a deep understanding of SQL semantics and domain-specific knowledge (Sen et al., 2019). Text-to-SQL systems must accurately interpret the metadata information of the entire database structure to correctly execute complex BI queries (Sen et al., 2019; Wong et al., 2021). The development of Natural Language Interface to Database (NLIDB) systems requires extensive training data that includes both SQL protocols and corresponding natural language text corpora. Database-specific ontologies are required for the effective use of NLIDB systems (Joshi et al., 2020; Katsogiannis-Meimarakis & Koutrika, 2023). Another challenge is the universality of the solutions, as NLIDB systems struggle to correctly recognize and translate queries when applied to databases with specific terminology for which they have not been trained.

Challenge 4 (C4): Outdated corporate culture. Current research increasingly emphasizes the importance of a data-driven corporate culture for the successful implementation of AI-supported BI systems. This type of culture is essential to make decisions based on quantitative and empirical insights and to promote the adoption of solutions emerging from enhancing BI systems using AI (Andriole & Barsky, 2022; Anisuzzaman et al., 2022). The absence of a flexible, data-driven culture can lead to decisions being made without sufficient quantitative foundations, undermining the very purpose of BI systems (Andriole & Barsky, 2022). Furthermore, cultural differences between different departments of an organization can hinder the effective use of BI systems (Figalist et al., 2020).

Challenge 5 (C5): Misclassification from inadequate training data. The critical element for the application of AI to enhance BI systems is the amount of data available (Nugroho & Surendro, 2019). The effectiveness of AI models depends on equivalence of data quality and quantity (Merhi, 2023). This applies to both predictive and prescriptive models as well as NLP algorithms in the context of augmented analytics (Katsogiannis-Meimarakis & Koutrika, 2023; Nugroho & Surendro, 2019). Poor data quality and quantity can increase the likelihood of mis-classification and thus increase the susceptibility to bias in the models, especially if the training data itself contains bias (Anisuzzaman et al., 2022; Brynjolfsson & Mcafee, 2017; Prat, 2019). Checking data quality is therefore essential in all phases of AI system implementation (Merhi, 2023).

Challenge 6 (C6): Changing roles and range of tasks. The rapidly evolving landscape of AI-supported BI presents users with challenges that require adaptability and the acquisition of new skills. The requirements for BI users are constantly changing. Knowledge of data management, functional programming languages and general statistics is becoming increasingly important. In addition, familiarity with concepts and the applicability of AI algorithms is important (Dong & Triche, 2020; Urbaczewski & Keeling, 2019). BI users must therefore constantly adapt their skills to keep up with the changing technological environment.

5. Results from Delphi Study

Figure 1 shows the relation of expert ratings on impact and likelihoods. Experts rated the opportunities regarding (1) their likelihood of occurrence until 2030 and (2) the impact on business practice. They rated the challenges regarding (1) their likelihood to be overcome by 2030 and (2) the impact on business practice as soon as they are overcome. Further, Figure 1 shows where a consensus was reached as the inter-quartile range of expert ratings was below or equal to 2. A consensus was reached for 9 out of 12 rated items (comprising six challenges and six opportunities).

Overall, opportunities have a higher likelihood of occurrence than challenges. The highest likelihood of occurrence of a challenge is 65% (C3) compared to 68% for the lowest rating of a potential (O4).

According to expert ratings, the opportunities with the highest likelihood of occurrence are facilitated information retrieval (O2) and increased speed of data analysis (O5). Both opportunities relate to facilitating daily operational BI practice based on AI reducing manual efforts and supporting typical BI processes. An acceleration of data analytical pipelines supporting BI will become a necessity to keep up with increasing data masses (Simitsis et al., 2023; Yan & He, 2020).

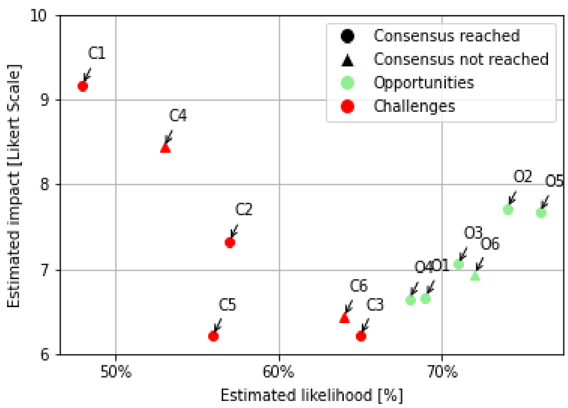

Figure 1. Relation of estimated likelihood and impact on business practice as rated by experts.

Moreover, the highest impact was assigned to overcoming the challenge of insufficient data quality (C1) and overcoming the challenge of outdated corporate culture (C4). Poor data quality has been identified as major inhibitor of progress in data analytics in various contexts (e.g., R. Zhang et al., 2019; Y. Zhang et al., 2023). Also, the need for cultural adjustment towards incorporating AI to take advantage in operational practice has been identified in related studies (Wamba et al., 2024). Interestingly however, both challenges have been attributed to the lowest likelihood of occurrence overall. That is, experts seem comparatively pessimistic about ways to overcome these challenges despite the entailed strong positive impact on BI.

6. Discussion and Implications

Our findings reveal six opportunities and six challenges that are consistently highlighted in both literature and by experts. In line with related research, we show that AI and BI are becoming increasingly intertwined transforming BI with AI advancements (e.g., Bharadiya, 2023a, 2023b). For example, related research shows that AI can leverage data analytical capabilities through machine learning, which corresponds to O5 (Chaturvedi et al., 2017; Khan et al., 2020). Going beyond, our literature analysis and expert interviews resulted in automation (O4) and predictive capacities (O6) of AI to enhance BI systems in terms of data analytics. Interestingly, although many publications focus on data analytical capacities in BI, the results from our Delphi study reveal opportunities with great estimated impact. For example, we find that data democratization using NLP to access data will increase information diffusion in companies as technical skills become less relevant (O2). On the other hand, our study also reveals challenges to overcome to establish competitive BI systems encompassing AI. In line with related research, we find that data quality is the major inhibitor for successful BI-system implementation and use (Balachandran & Prasad, 2017; Zelenka & Podaras, 2021).

In terms of *theoretical implications*, we find that the successful implementation of AI-supported BI systems needs both technological upgrades as well as an alignment of employee skills, mindset, and lastly organizational culture. This fosters the need for more research at the intersection of AI and BI from various socio-technical streams, such as strategic business and IT alignment, technology acceptance or task technology fit. Moreover, our results lay a foundation for the theory-induced creation of BI frameworks that incorporate AI. We find that key aspects of such a framework should be process acceleration, for example through automation (O1, O4, O5) as well as data democratization (O2, O3). Also, frameworks should consider impactful challenges such as increasing data quality (C1) or creating a suitable corporate culture (C4). Especially the challenges open opportunities for future practical research due to their high impact and practical relevance.

Likewise, we consider the need for prioritization of data quality improvements (cf. C1) a *practical implication*. BI practitioners would benefit from data quality improvements encompassing for example standardization of data formats as well as meta-data compliance (R. Zhang et al., 2019) as correctness of and confidence into BI reports would increase.

As a consequence, trust in model-induced analyses would be fostered and data literacy employees promoted with practical implications on corporate culture (C4).

A further practical implication results from a focus on efficiency gains in BI due to AI support (O5) reducing efforts as well as response times to (ad-hoc) reporting inquiries. To this end, our results entail the need to emphasize faster information access through AI-enhanced retrieval (O2) encompassing conversational analytics. AI-based data analysis for decision support constitutes a competitive edge through time and cost savings as well as faster reactions to irregularities (Eboigbe et al., 2023). Due to competitive pressure, harnessing opportunities to streamline processes end-to-end (cf. O2 and O5) will constitute necessities in the long term for BI practitioners.

7. Conclusion, Limitations, and Future Research

The vast proliferation of AI in various business contexts impacts how companies handle their data. In terms of its integration into BI, AI presents opportunities and challenges for data retrieval, collection, analysis, and interpretation. Based on a structured literature review, we identified six opportunities and six challenges that were rated by experts in a three-round Delphi study in terms of likelihood of occurrence and impact. Among other findings, our results emphasize the need to address a data-driven corporate culture as well as high data quality standards.

The interpretation of our results should be informed by the methodological limitations of our study. First, the structured literature review is subject to interpretation by the researchers as is the process of exclusion of publications. Researchers from other contexts might infer other results from the literature and even include other publications. However, we adhered to guidelines specific for Information Systems (vom Brocke et al., 2009). Also, we coded the identified literature with two independent researchers.

Second, our findings rely on the perspectives of a limited group of experts from practice. The limited number of participants leaves the possibility of biases. While the ratings offer valuable insights into the relative importance of items, we lack understanding of the rationale behind specific ratings. However, we built our methodology on established practice from literature (Häder, 2014).

Future research may mitigate these shortcomings by conducting larger studies of quantitative and qualitative nature to infer statistical significance of the results and explore reasons behind ratings.

Additionally, we find that acceleration of processes as well as broader data access require investigations for effects of proliferating (real-time) data on users and their perception of information systems as well as their preferences of information system design (e.g., Stahmann, 2023; Stahmann, Gravemeier et al., 2023; Stahmann, Rodda, & Janiesch, 2023).

Moreover, despite emphasis in literature, expert ratings show lacking consensus in terms of AI-based predictions (O6), outdated corporate culture (C4), and changing roles and range of tasks (C6). While the lack of consensus may be due to the high complexity of these points, they seemingly require a practically focused discussion in terms of their relevance and impact. They may require further investigation in terms of why there is a lack of consensus and an outlining of future pathways for their investigation and practical implementation. Especially AI-based predictions (O6) have received high focus in scientific and practical literature. Future research needs to examine how to increase attention for these and how their diffusion practical BI can be increased.

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