Exploring the Benefits, Challenges, and Opportunities of Collaborative Business Intelligence

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Abstract

In traditional business intelligence (BI) settings, the collective decision-making process is often hindered by the absence of knowledge and expertise exchange among various stakeholders, as well as lack of information sharing. The study delves into the concept of Collaborative BI, which aims to overcome these limitations by promoting collaboration, business networking, knowledge sharing, and improved communication among stakeholders. Based on a systematic literature review, the study explores the notion of Collaborative BI, formulates its definition, and reports on its challenges, benefits, and limitations. It also provides an insightful overview of Collaborative BI landscape and multiple advantages it can deliver to modern business organizations. The study also acknowledges potential threats to the validity of its findings due to the limited scope of the literature review. Finally, the study highlights the need for further research to address the limitations and expand our understanding of the CBI field.

Keywords: Business Intelligence, Collaborative Business Intelligence, Benefits, Challenges

1. Introduction

Making managerial decisions is a complex issue that requires both experience and intuition, as well as profound analytical knowledge (Davenport & Harris, 2017; Drucker, 2007). It is emphasized that the decision-making process should also be based on extensive collaboration, cooperation, and communication between different actors. It is believed that not only the management of a given organization has an important role in making decisions, but also its stakeholders, including customers and suppliers. Their voice and knowledge are vital in solving socioeconomic issues. Therefore, modern organizations have to deal with processing and analyzing huge amounts of information from various sources and create conditions for practical cooperation between many people and external institutions (Davenport et al., 2010).

Business Intelligence (BI) systems are recognized today as one of the most significant technologies supporting the decision-making process in organizations at all levels of management (Laudon & Laudon, 2004; Olszak, 2020). Their distinguishing features have become such components as data warehouses, OLAP analyses, data mining, and dashboards. These components enable the comprehensive integration of data from various sources, their in-depth analysis and exploration, and the discovery of new knowledge, as well as data reporting and visualization. Recently, BI systems linked to Big Data technology have been considered an important analytical tool, enabling the creation of a comprehensive image of the enterprise and its environment (Olszak & Zurada, 2019).

When analyzing the utilization of BI systems in various organizations, several observations and comments come to mind. A noticeable drawback of these systems is insufficient support for decision-makers in the field of collaboration, cooperation, networking, and exchange of ideas, discussion, and knowledge sharing. In connection with the above, there is an urgent need to create and utilize in organizations a new generation of BI systems, referred to as Collaborative Business Intelligence (CBI).

The theoretical aim of the work is to investigate a Collaborative Business Intelligence issue and to examine the main benefits and challenges faced by organizations before utilizing CBI.

URI: https://hdl.handle.net/10125/106408
978-0-9981331-7-1

To attain the defined research goal, the paper is structured as follows. In Section 2, we describe the development history of BI systems and their various generations. Additionally, we characterize the most significant advantages and limitations of the existing BI systems. In Section 3, we elaborate on the research methodology employed in this study. In Section 4, we review and synthesize the state-of-the-art literature. Finally, in Section 5, we put forward the contributions of the study, along with threats to validity and future research directions.

2. Background

The development history of information systems aimed at supporting managerial decisions is rich and dates back to the last century (Bonczek et al., 1980; Bui, 2000). Their special role was marked when managers faced the need to: (1) use a lot of data, often coming from different sources, (2) operate historical data and aggregated data, (3) constantly monitor the implementation of actions taken, and (4) anticipate future and long-term plans.

The first BI systems were focused on simple reporting and static data analysis (Olszak, 2016). Over time, they began to enable data integration, multidimensional analysis (On-Line Analytical Processing, OLAP), prediction and discovery of new relationships between data, visualization of the most important indicators, monitoring and alerting (Business Activity Monitoring), as well as strategy modeling and performance management (Business Performance Management), and processing and analysis of large data sets (Fig. 1).

BI systems assume that information and knowledge are strategic resources, and advanced analytics allows quick decision-making, discovering new business opportunities, and identifying factors that determine the further development and success of the organization (Skyrius & Skyrius, 2021). From the procedural point of view, it can be assumed that BI systems generate various reports or calculate Key Performance Indicators (KPIs) based on which hypotheses are formulated and then verified by detailed analyzes (Alsqour et al., 2012).

An in-depth analysis of the literature shows that there is no universal definition of the term "Business Intelligence" (Chen et al., 2012; Ul-Ain et al., 2019). It is usually assumed that it is a broad category (compared to an umbrella) covering technologies, applications, and various processes responsible for collecting, storing, accessing, analyzing, and visualizing data that help make more effective decisions at all levels of management. Data warehouses, OLAP techniques, data mining, as well as techniques for data reporting and visualization are primarily utilized for this purpose.

The nature of Business Intelligence systems can be better understood by analyzing the most important generations of their development. BI 1.0, BI 2.0, and BI 3.0 generations are usually indicated in this context (Olszak, 2020). The BI 1.0 generation has its roots in database management systems and data warehouses. These technologies enabled more effective data reporting, data visualization (dashboards), querying databases (ad hoc query), creating integrated data repositories, quick data search, creating scorecards, predictive modeling, and data mining.

The early 2000s, which were mainly related to the dynamic development of the internet, various search engines, social media, text and natural language processing, initiated the development of the BI 2.0 generation. For example, by analyzing customer clicks and their logs, tools such as Google Analytics provide interesting information on user activity, reveal their shopping preferences and interests, and enable optimization of product placement, analysis of customer transactions, and market structure analysis. Many web 2.0 applications are built based on social media content – mainly blogs, social networking sites, multimedia sites, virtual reality, and games (Plikynas et al., 2022).

Generation 3.0 is primarily associated with the development of smartphones, tablets, and devices equipped with RFID. It allows users to process content from various multifunctional mobile devices. Cloud services, Big Data processing, streaming processing, and real-time processing are becoming the standard (Olszak & Zurada, 2019). It seems possible to create innovative applications and intelligent networks for everyone and generate new relationships between organizations, customers, suppliers, and shareholders. According to several authors (Chen et al., 2012), five core attributes support BI 3.0 philosophy: proactive, real-time, integrated with business processes, operational (available to line workers), and extended to reach beyond the boundaries of organizations to improve information delivery and decision support functionality for all. In other words, BI 3.0 focuses on building collaborative intelligence, expert networks, communities of practices, knowledge sharing, developing good practices, and business patterns.

Looking at the use of BI systems, it is hard not to notice that various reasons (causes) underlie their utilization in organizations. Three goals are usually indicated (Wixom & Watson, 2010). These are: (1) improving work in individual departments of the organization (e.g., marketing, sales) and effective management of advertising campaigns, analysis of

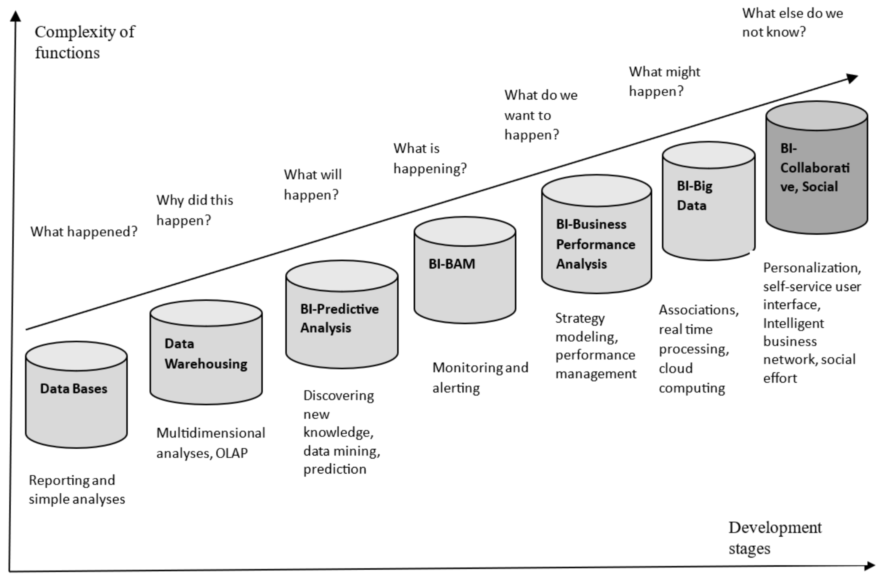

Figure 1. Development of Business Intelligence systems.

product profitability and customer behavior; (2) creating an IT infrastructure that will ensure effective data collection and cleansing, their integration and analysis in various systems and perspectives; (3) carrying out transformations and changes in organizations involving the introduction of new, analytics-based business models, as well as new forms of collaboration and cooperation with customers, suppliers, and other stakeholders (Guan et al., 2014).

The analysis of the literature and experience gained from business practice indicate that BI systems are becoming indispensable tools for the work of modern organizations. Not only do they enable simple reporting and data analysis, but also new knowledge discovering, monitoring and forecasting events, and performance management. At the same time, it should be noted that there is a growing need to involve various stakeholders in the decision-making process. It is believed that they are a vital element in creating collective intelligence and designing innovative business models based on mutual trust and cooperation. Their knowledge and experience contribute to increased management efficiency and more effective decision-making (Shi et al., 2017).

3. Methodology

In our study, we employed a systematic literature review (SLR) as the research method. SLR is a defined and methodical approach used to identify, interpret, evaluate, and synthesize existing research evidence in order to investigate a specific issue by addressing explicitly defined question(s) (Wahono, 2015; Xiao & Watson, 2019). We report and present the results in the form of a table, organized according to the publication time of the papers. To conduct this review, we followed the methodology proposed by (Denyer & Tranfield, 2009), which consists of five steps: (1) review and formulation of the research question, (2) location of relevant studies, (3) selection and evaluation of the identified studies; (4) analysis and synthesis of the findings; and (5) reporting of the results.

3.1. Research Question Definition

The first goal of our study is to explore the concept of Collaborative Business Intelligence (CBI) and gain a comprehensive understanding of this notion. The second goal is to identify the anticipated or documented benefits of implementing CBI solutions. To accomplish these goals, we propose the following two research questions:

RQ1 How has the term of Collaborative Business Intelligence been defined?

RQ2 What are the benefits, challenges, and opportunities associated with the implementation of Collaborative Business Intelligence?

3.2. Data Source and Search Strategy

All pertinent literature relevant to our study topics was meticulously selected and searched using four distinct data resources, depicted in Table 1.

Table 1. List of the data sources used.

Name	URL
ACM digital library	dl.acm.org
IEEE Xplore digital library	ieeexplore.ieee.org
Scopus	scopus.com
Web of Science	webofknowledge.com

3.3. Search Query Definition

Firstly, we generated a list of the keywords for the document search based on the research goal, specifically derived from the research questions. Secondly, we adhered to query formulation guidelines tailored to each database engine, incorporating the usage of Boolean operators (e.g. AND, OR, AND NOT) and quotation marks. Since there were no exact or closely related terms, no wildcards were defined. As a result, a single search query was formulated (see Table 2) that encompassed both research questions. It is important to note that when executing the search queries on each database, the query ("Collaborative Business Intelligence" AND "Benefit"), yielded zero search results. These searches were conducted in April 2023.

3.4. Inclusion and Exclusion Criteria

In the first step, we established two inclusion criteria (IC) as follows: (IC1) the document type must be a peer-reviewed journal article or a conference proceeding, and (IC2) the document must be written in English. After applying these inclusion criteria, the number of the search results is provided in the column (I) of Table 2.

Subsequently, we merged the search results from all databases, resulting in a consolidated list of 32 papers. To ensure uniqueness, we sorted the list was by title in ascending order and conducted a manual analysis of both the title and abstract. This process enabled us to identify and remove a total of 10 duplicate papers. As a result, we were left with 20 unique papers, including 3 from ACM, 3 from IEEE, and 14 from Scopus. Notably, there were no papers retrieved from Web of Science. Interestingly, we encountered two papers that were published under different titles but had nearly identical abstracts. As a result, the latter paper was classified as a duplicate and subsequently removed from the list. The final results are depicted in column (II) of Table 2, indicating the respective results for each data source.

To identify relevant papers aligned with the focus of this review, all three researchers conducted a comprehensive screening and analysis of the titles and abstracts of the extracted 21 records. This screening process followed three exclusion criteria: (EC1) the full version of the document was not accessible through subscription from our institutions or the associations we are members of; (EC2) the research methodology applied was either a literature review or a systematic literature review; (EC3) the study did not pertain to the topic of Collaborative Business Intelligence.

The classification schema applied consisted of two mutually exclusive categories: relevant and irrelevant. In cases where there was doubt or uncertainty, each researcher independently read the paper carefully. Furthermore, in situations where further doubt or lack of full agreement persisted, a collaborative analysis and evaluation took place through online discussion.

3.5. Data Extraction

A total of 11 papers (1 from ACM, 1 from IEEE, and 9 from Scopus) were classified as relevant, as indicated in column (III) of Table 2. These articles were published between 2008 and 2019.

Due to the relatively small number of identified papers, we employed a snowballing strategy to ensure the inclusion of any potentially missing relevant papers. The snowballing technique involves backward snowballing (BS) and forward snowballing (FS), which refer to exploring a paper's references and citations, respectively. For each paper of the 11 relevant papers, we reviewed their reference sections and used Google Scholar to determine the number of citations. It is important to note that when multiple records were returned by the search engine for a single publication, the citations from all listed records were combined. This proces was performed on May 5, 2023, and the details of this examination are presented in Table 3.

The examination yielded a total of 526 documents as inputs for further analysis. Similar to the primary search, we used the same methodology, scanning the titles, abstracts, and keywords of the snowballed papers. These documents underwent both inclusion and exclusion criteria, as previously applied. Additionally, one more paper was classified as relevant. Ultimately, a total of 12 papers were identified as relevant. These 12 papers were sorted in ascending order based on their year of publication and are discussed and referenced in Section 4 of the study.

4. Results

To capture the broad and fundamental concepts and relationships associated with Collaborative Business Intelligence, we manually extracted keywords provided by the authors of relevant papers. Next, we carefully assessed each keyword and assigned it to its corresponding concept. However, we excluded

Table 2. The summary of the data extraction stage.

Search Query / Data Source / Step	ACM			IEEE			Scopus			WoS		
	I	II	III	I	II	III	I	II	III	I	II	III
”Collaborative Business Intelligence”	3	3	1	3	3	2	18	14	9	8	0	0

I: number of the search results; **II**: number of the search results after duplicates removal; **III**: number of the relevant papers.

Table 3. The estimated number of references and citations of the 11 papers, extracted by the SLR procedure.

Paper ID	#Ref.	#Cit.
Dayal et al. (2008)	6	21
Berthold et al. (2010)	21	71
Mettler and Raber (2011)	22	21
Golfarelli et al. (2012)	15	7
Martins et al. (2012)	24	10
Rizzi (2012)	42	37
Kaufmann and Chamoni (2013)	16	2
Teruel et al. (2014)	10	12
Stefanovic (2015)	30	57
Liu et al. (2017)	26	14
Teruel et al. (2019)	49	13
Sum	**261**	**265**

certain terms like ”centralized ontology,” ”hospital,” ”logistics management,” and ”supply chain inventory management” as they were not directly related to the core categories or associated concepts. Additionally, we disregarded terms like ”controlled experiment,” ”goal-oriented requirements,” ”I-Star,” ”Architecture,” ”OLAP,” ”requirements,” and ”web portal” as they either pertained to specific study goals or fell outside the general scope of the Collaborative Business Intelligence domain. To streamline the concepts, we merged synonyms into a single concept. For example, ”P2P architectures” and ”peer-to-peer architectures” were consolidated. Lastly, we eliminated the terms ”collaboration” and ”business intelligence” as they already form the foundation of our area of interest. Overall, this process identified a total of 14 unique concepts, illustrated in Figure 2.

RQ1. **How has the term of collaborative business intelligence been defined?**

For Dayal et al. (2008) collaborative business intelligence combines business intelligence and collaboration technologies to support decision making by bringing together the knowledge and expertise of multiple stakeholders. The paper outlines the requirements for collaborative BI and provides a use case example of managing a large data center. The authors also introduce a prototype collaborative BI platform developed at Hewlett-Packard Labs that incorporates visual analytics, multi-modal interaction technologies, and 3-dimensional virtual rooms for collaboration. The platform also incorporates richer metadata models, including modeling the knowledge of human experts.

Berthold et al. (2010) did not explicitly define the term of CBI. They proposed an integrated collaboration environment which will enable dispersed users to share and exchange information from various private and public sources and undertake collective decisions on-the-fly as if users would work together in the same room. The authors proposed a low granularity CBI architecture framework that includes end users, ad-hoc collaborative analysis, integration and enrichment, data sources, and the global business data model.

According to Mettler and Raber (2011), there was no formal definition of CBI. The paper presented a process-centric, CBI system to aid an organization in enhancing delivery reliability and improving supply chain of goods in business networks comprising hundreds of suppliers and partners worldwide. Delivery reliability is a key factor in achieving competitive advantage in the machinery industry. A conceptualized solution architecture involves central message exchange system focused on analytical knowledge sharing and information exchange. This platform needs to be seamlessly interfaced with existing ERP, supplier relationship management (SRM) or e-business systems and integrated into business processes of manufacturers and suppliers.

Golfarelli et al. (2012) proposed framework for CBI involves a Peer-to-Peer (P2P) network of heterogeneous peers that share OLAP query answering functionalities. The goal is to enable data sharing and cooperation among companies and organizations. In this framework, when a user submits an OLAP query on a peer, the query is reformulated on other peers by using mappings between the multidimensional schemata of the peers. This enables the user to access a wider range of business information beyond their own company’s data.

Martins et al. (2012) do not define what CBI is. The study proposed the framework for a systemic CBI architecture based on the centralized ontology repository of concepts and distributed data services that is able to combine diverse information and provide data to general analytical queries. The foundation of

Figure 2. Foundational Ontology for the Collaborative Business Intelligence.

this architecture differs from a traditional BI system in two aspects. First, it is based on the integration of heterogenous semantic concepts to build upper ontologies comprising general terms that are common across all domains. Second, source data retrieval in terms of low coupling and abstraction is achieved by following Service Oriented Architecture (SOA) procedures.

Rizzi (2012) claims that the role of the proposed CBI system is to expand the decision-making process beyond the organization borders by data sharing and cooperation with other organizations. The data warehouses integration approaches, namely, warehousing, federative, and peer-to-peer are investigated as enabling methods for CBI. A new peer-to-peer platform, called Business Intelligence Network (BIN), allows one to formulate queries and share business information for decision-making. The CBI system is characterized by scalability, lack of centralization, and independence of peers.

For Kaufmann and Chamoni (2013) Online Social Networks (OSNs) are becoming increasingly popular for exchanging information between human actors, and they have the potential to provide valuable insights for companies in their CBI efforts. Traditionally, BI systems rely on structured and pre-filtered data, but OSNs offer an opportunity to tap into unstructured data and gain a better understanding of customers. A small prototype has been developed to demonstrate the feasibility of this approach.

According to Teruel et al. (2014), in many organizations, the process of CBI involves individuals exchanging information via email and documents. However, this method can be inefficient and prone to errors, as important information can be lost or misinterpreted in the process. The framework proposed in this paper aims to improve the current practice of CBI by providing a structured approach for modeling, eliciting BI requirements, and eliciting the participants, goals, and information needs involved in the decision-making process.

Stefanovic (2015) proposed the use of data mining technology for supply chain inventory management, as traditional inventory management approaches and technologies are not adequate for the current business environment. The proposed approach involves the use of a unified CBI semantic model and a data warehouse to provide accurate and up-to-date information for better inventory management decisions.

Liu et al. (2017) aimed to apply CBI to hospital supply, processing, and distribution (SPD) logistics management in China. It proposed a layered structure for a CBI system and built a data warehouse to support it. The study leveraged data mining techniques such as SVM to solve key problems in hospital logistics CBI system. Finally, the study researched collaborative techniques oriented towards data and business process optimization to improve the business processes of hospital logistics management.

The idea behind self-service BI (SSBI) is to empower casual users with the tools and capabilities to independently perform data analyses and reporting. This approach would foster simplified, more agile, and efficient decision-making processes. Passlick et al. (2017) conducted a thorough review of existing literature, which formed the foundation for developing an initial SSBI model. The model was subsequently refined through qualitative data analysis gathered from interviews with 18 BI and IT experts working in various industries. The resulting model demonstrated the interaction between the self-service elements introduced and the traditional components of BI. For instance, it explored the integration of collaboration rooms and a self-learning knowledge database, which served as a source for a report recommender system.

Teruel et al. (2019) claim that the current state of CBI in enterprises, which is based on exchanging emails and documents between participants, leading to information loss and poor decision-making. To address this impediment, the study proposes a modeling language to elicit and model the goals and information needs of participants in CBI systems, based on innovative methods to elicit and model CBI and BI requirements.

A synthesis of the above-discussed works leads us to define Collaborative Business Intelligence as a *cutting-edge environment that integrates modern Business Intelligence (BI) tools and collaboration technologies. This environment enables different stakeholders to share expertise and knowledge as well as exchange real-time information from internal and external sources, supporting companies in making informed, collective, and actionable business decisions in a timely manner*.

RQ2. **What are the benefits, challenges, and opportunities associated with implementing collaborative business intelligence?**

Dayal et al. (2008) state that to advance the field of CBI the following six challenges remain to be addressed. Modeling the knowledge of human experts and associating it with activities in business and operational processes. Capturing metadata from heterogeneous structured and unstructured data sources. Automating the creation of ontologies. Developing algorithms for real-time analytics over event streams. Detecting when analytic models are out of date and incrementally updating them. Optimizing the system end-to-end to ensure real-time response to events. Recording and analyzing collaboration sessions to discover interaction patterns.

For Berthold et al. (2010) in order to make timely and sound decisions, it is often imperative to carry out ad-hoc analysis in a collaborative way including stakeholders such as customers, suppliers, and domain experts to name a few. Current BI solutions fail to achieve these goals because they are hampered by inadequate communication means which mainly rely on emails and phone conversations.

According to Mettler and Raber (2011), in agile business networks of manufacturing industry, collaboration is often impeded by be loosely-coupled, ill-managed and ineffective relationships between stakeholders such as manufacturers and suppliers. As a result, the delivery of ordered materials is not supervised or tracked properly leading to increased operating expenses and delays.

Golfarelli et al. (2012) proposed framework allows for more efficient and effective decision-making by leveraging the collective intelligence of a network of peers. By sharing business information and knowledge, companies and organizations can gain insights and make better-informed decisions. This approach enables the users to access a wider range of business information beyond their own company's data. The results are presented to the user in a format that can be easily interpreted and analyzed.

Martins et al. (2012) claim that traditional BI solutions are often restricted to specific domain data and information tables. They also support massive data loads provided by other companies in local warehouses. This leads to information not being obtainable on-time or being misinterpreted. The authors of the proposed architecture reveal some concerns about its performance, capacity to fully automate tasks in the aligning and merging processes. The latter is the activity that may involve a human intervention, which could be reduced by ontology layer is improved.

For Rizzi (2012) the main resource-consuming issues, which were identified in the proposed BIN system, are timely answering queries and the number of messages exchanged between peers. Other challenges include implementing data fusion functionalities to reconcile the multidimensional results returned by peer queries, data source and quality, and advanced approaches to security related to data access and data sharing policies.

Kaufmann and Chamoni (2013) state that OSNs can serve as a platform for collaboration and communication among BI analysts. By using OSNs to connect and discuss findings, analysts can improve their analysis process and make more informed decisions. Overall, integrating OSNs into the BI process can offer a new perspective and enhance collaboration among analysts, leading to more accurate and comprehensive insights.

Teruel et al. (2014) argue that their framework can help avoid information loss, ensure that all relevant participants are included, and facilitate effective collaboration. The use of state-of-the-art approaches for modeling collaborative systems and eliciting requirements can enhance the accuracy and completeness of the framework, making it a valuable tool for enterprises looking to improve their collaborative decision-making processes.

Stefanovic (2015) presented an integrated model, semantically-rich, scalable, and flexible. The information is delivered to relevant decision makers in a user-friendly manner. Experiments carried out with real data from the automotive industry showed very good accuracy and performance of the model, making it suitable for collaborative and more informed inventory decision making.

Liu et al. (2017) claim that the proper combination of SPD model and BI system will improve the management of logistics in hospitals, reduce logistics expenses, and improve the quality of healthcare. The actual model implementation requires (1) innovative and improved plans and schedules for the application of BI system according to the actual situations of hospitals, (2) the collaborative participation of all internal departments in hospitals, and (3) timely response from external suppliers.

Though opinions of BI and IT specialists were instrumental in improving the initial SSBI model, more experts would be desired to offer their advice (Passlick et al., 2017). Also, it would be advisable to consider opinions from business users and different business sectors. Furthermore, the SSBI architecture would have to be customized for every company depending on its size and domain in which it operates. One more concern, mainly relevant to small companies, was related to the realization of a self-learning database, which might not have enough input data in terms of the number of reports, inquires, and analyses for the algorithm to learn and recommend solutions. The cloud-based knowledge database, which would contain reports and analysis from many companies, was proposed as a solution.

The approach, adopted by Teruel et al. (2019), was validated through a controlled experiment, which showed its understandability, scalability, efficiency, and user satisfaction. The proposed framework provides clear guidelines for collaborative tasks, participants, and information sharing, making it easier to trace every element needed in decision processes, avoiding information loss, and facilitating collaboration among stakeholders.

We will now recapitulate the insights provided by the literature on this subject. The papers examined and addressed a range of challenges, benefits, and limitations concerning CBI and its impact on the decision-making processes. Some of the challenges identified include knowledge modeling, capturing metadata, ontology automation, real-time analytics, model updates, system optimization, and communication barriers hindering collaboration. Privacy concerns, data integration issues, and user adoption also pose challenges in implementing CBI.

On the other hand, the benefits of CBI include improved decision-making, enhanced collaboration, increased organizational agility, and leveraging collective intelligence through sharing business information. It also offers the potential for improved logistics management, accuracy in inventory decision-making, and collaboration within agile business networks.

However, there are also limitations to consider. Data quality issues, security risks, and the complexity of integrating multiple data sources are common challenges. Traditional Business Intelligence (BI) solutions may have limitations in handling specific domain data, timeliness, and interpretation issues. Cultural barriers, organizational resistance, and the need for skilled personnel further impact the adoption and implementation of CBI.

5. Discussion

Our review focused on addressing questions related to CBI. In our opinion, this area still has significant gaps in knowledge that can only be illuminated through future research. However, what is particularly appealing is that we also envision other research avenues that are worth exploring through the theoretical lens of information systems theory.

5.1. Study Contribution

This study presents a new view on the issue of BI, analysing it from the perspective of collaboration, cooperation and communication. While previous research has not sufficiently highlighted the impact of CBI on the decision-making process, we argue that it can be a vital component in creating collective intelligence, designing innovative business models based on trust and cooperation, ultimately leading to improved business efficiency.

This study has two main contributions, which can be summarized as follows. Firstly, it serves as a review of the limited literature that examines the notion of CBI and systematically formulates its definition. Secondly, this review provides an insightful overview of the CBI landscape, focusing on its significant contributions to modern business organizations by delivering multiple advantages and addressing the challenges they face. More broadly speaking, our study contributes to the field of information systems theory (IST) by introducing a new conceptualization of CBI and advancing our knowledge regarding the benefits, challenges, and opportunities documented to date.

The theoretical implications relate to an in-depth discussion of the nuanced nature of the implementation of CBI for effective knowledge dissemination and the instrumental value of the stakeholders involved in relation to the state of the literature. The practical implications cover a range of benefits, challenges and opportunities that are of considerable value to any organization considering implementing CBI.

5.2. Study limitations

The snowballing procedure initially yielded 526 documents; however, upon closer examination, only 12 of these proved relevant for our in-depth analysis. This could potentially be attributed to the emerging nature of the CBI field, which might not have garnered substantial attention from researchers thus far. Our approach to the SLR adhered to well-established guidelines, and we meticulously searched reputable sources, including ACM, IEEE Xplore, Scopus, and Web of Science. Admittedly, the limited number of articles available for analysis might not be considered extensive by conventional standards. Nonetheless, this scarcity could potentially serve as the foundational groundwork for future studies that seek to propel the advancement of CBI. Consequently, we acknowledge that the scope of our findings is inherently limited due to the constrains stemming from the restrictive article pool.

5.3. Threats to Validity

First and foremost, in this case, one should seriously consider the construct validity, which is defined as the identification of issues related to the applied research settings. In general, when comparing the topic of study with the formulated search query, they are perfectly aligned, ensuring a strong overall validity assessment. However, since no synonyms were identified or alternative search queries executed, one could consider the scope of the analysis relatively limited. Regarding external validity, the question of generalizing the results of the systematic literature review (SLR) poses a potential threat. However, the use of well-recognized scientific data sources provides necessary evidence in this context. Furthermore, providing all the relevant details related to the applied guidelines further strengthens the validity. Nowadays, SLR is widely employed as a qualitative methodology in IST research. The reliability of the results has been established through repeated and independent analyses, encompassing the initial run of searching and data extraction, as well as the subsequent run of reading and organizing the content.

5.4. Future Research Directions

Undoubtedly, the topic of Collaborative Business Intelligence requires further research efforts to achieve a theoretical consensus. Additionally, lessons learned from practical implementations of CBI, including discussions on how they have contributed to business performance, as well as the challenges encountered and how they were overcome, hold significant importance for decision-makers, considering both economic and organizational factors.

Given that information needs vary among individuals and groups of stakeholders, it becomes a crucial component in building a data-driven organization. Thus, exploring barriers to data-driven business adoption, particularly those related to managerial and cultural aspects rather than data and technology, emerges as the first avenue of research.

Considering the increasing enterprise push for data literacy and the strong interest in fostering collaboration among various business users, it appears valuable to investigate the possibilities of integrating existing technologies to enhance information culture. Thus, exploring the capacity for application integration and data integration becomes the second avenue of research.

Lastly, the ongoing shift from office-based work to remote home work has significantly reduced obvious measures of instant communication and collaboration. As a result, numerous systems and tools have emerged to enable teams to share thoughts and ideas, allowing members to effectively stay on track with their goals and tasks. However, in the context of CBI, only a few studies have examined the impact of such a shift on work quality, employee motivation, or performance. Therefore, these issues should be considered as the third avenue of research.

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