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THE INTERSECTION OF ARTIFICIAL INTELLIGENCE AND BUSINESS INTELLIGENCE – A SYSTEMATIC MAPPING STUDY

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ABSTRACT

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The research fields artificial intelligence and business intelligence have been growing in popularity in recent years. In the modern digital landscape, the data is continuously increasing. Traditional BI tools are not designed to handle large volumes of data. The integration of AI into BI can mitigate this problem. By extracting value from unstructured data with AI and BI, organisations can be more productive, make better decisions, understand market conditions. The combination of AI and BI can be highly beneficial for companies. However, the combination of the research fields is relatively new and mapping studies have been absent so far. This thesis contributes to this research gap. In this thesis a systematic mapping study has been conducted on the two research themes artificial intelligence and business intelligence. The goal of the study was to provide a comprehensive understanding/overview of the existing research landscape, research trends, and identification of potential areas of future exploration in the domain of AI-BI. The study collected 121 accepted articles from numerous journals and conferences, revealing a fragmented yet evolving research landscape with no dominant methodologies. The findings highlight key research gaps, particularly in validation research and AI ethics within the AI-BI domain. The study also emphasizes the significant academic implications of AI and BI integration, including the need for interdisciplinary research approaches and standardized methodologies. Industry implications point towards leveraging AI for enhanced predictive analytics and decision-making in diverse sectors such as retail, e-commerce, healthcare, and finance. These insights are critical for informing future research directions, shaping industry practices, and guiding educational strategies in the rapidly advancing field of AI and BI.

Keywords: Machine Learning, Artificial Intelligence, Business intelligence.

FIGURES

TABLES

TABLE OF CONTENTS

1 INTRODUCTION

This thesis investigates the intersection of the research fields artificial intelligence (AI) and business intelligence (BI). In the last decade, there has been an increasing interest in Business Intelligence. Research indicates that organisations can obtain the benefits of: customer understanding, business insight, cost reduction, and competitive edge by adopting BI (Marilex et al., 2018). The current landscape is rapidly evolving, and the decision-making process differs significantly from what it was a decade and a half ago. Gartner's research has shown that 65% of contemporary decisions are more intricate than those made just two years ago (Rollings, 2021). In this evolving landscape, BI plays a crucial role in facilitating the resolution of intricate decisions. Despite its considerable benefits, BI also presents a range of challenges (Gudfinnsson & Strand, 2017).

One notable trend is the growing role of machine learning (ML) in business intelligence. The rise of the internet of things has led to an abundance of data, more and more information becomes available which expands the potential of BI to provide value for organisations. With the advent of big data and the rise of artificial intelligence. the importance of BI has grown substantially. Surprisingly, despite the amount of data available, a significant portion, approximately 68% remains untapped within organisations (Seagate, 2020). This statistic showcases the untapped potential for organisations to improve their operation, decision making, reduce costs, and gain insights if they can effectively analyse this data.

Conventional/traditional BI systems are not designed to handle large volumes and as data continues to grow exponentially, BI's limitations become increasingly evident. Consequently, the integration of machine learning becomes imperative for effective data analysis. There are large amount of unstructured data that can not be analysed by conventional BI tools, but machine learning can help analyse the data.

Machine learning, a subset of artificial intelligence, has made remarkable strides in the past few decades. New discoveries continually emerge on how AI can enhance business operations. AI applications, especially in machine learning, can enhance BI by enabling automatic text summarizations for complex business reports, which, according to Naidoo & Dulek (2022), have shown moderately satisfactory results. However, the ongoing improvements and advancements in the field suggest the potential of AI/ML in aiding BI is high.

ML plays a transformative role in BI revolutionizing the research field and how companies analyse their data (Bharadiya, 2023b, 2023a). AI/ML technologies can enhance BI by enabling predictive analytics, automating data cleansing processes, enabling the understanding and process of human language, anomaly detection, real time insights, automated report generation. As such, it is becoming increasingly clear that the integration of ML and AI technologies can play a significant role in enhancing the efficacy of BI.

ML includes all the approaches that allow machines to learn from data without being explicitly programmed. ML is based on the notion that machines are capable of learning from data, spotting patterns, and making decisions with little human intervention. ML ability to discover patterns in data that may elude human perception is particularly valuable, especially in the context of big data, where the sheer volume of data exceeds human analytical capabilities. The need for the analysis of large datasets becomes increasingly important for BI as these datasets grow. According to John Rydning, "*The Global DataSphere is expected to more than double in size from 2022 to 2026,*" (Rydning, 2022).

Waller & Fawcett, (2013) have highlighted the scarcity of literature on topics such as data science, predictive analytics and big data, emphasizing the need for additional knowledge. This study aims to address this knowledge gap and provide new insights for this domain. While there has been a rapid increase in published research articles, the research fields of Artificial Intelligence and Business Intelligence lack a comprehensive overview of the current state of research. The research field of AI-BI is maturing and there is a steep increase of publications in the last decade. However, mapping studies within this field have been absent. By offering an evidence-based perspective on the research field, this study empowers researchers to identify major research topics and areas that have received limited attention. Consequently, researchers can prioritize areas that require further exploration and focus.

This study applies systematic mapping to explore the intersection of two key themes: Business Intelligence and Artificial Intelligence. Figure 1 illustrates the intersection between these two research themes. In order to proceed with systematic mapping, it is essential to clearly define these themes. Therefore, chapter 2 will provide more detailed descriptions of these two themes. Chapter 3 describes method of systematic mapping. In chapter 4, the results are presented. In chapter 5 the results are being discussed, and recommendations for future research will be given. And finally, chapter 6 contains the conclusion and summarizes the thesis.

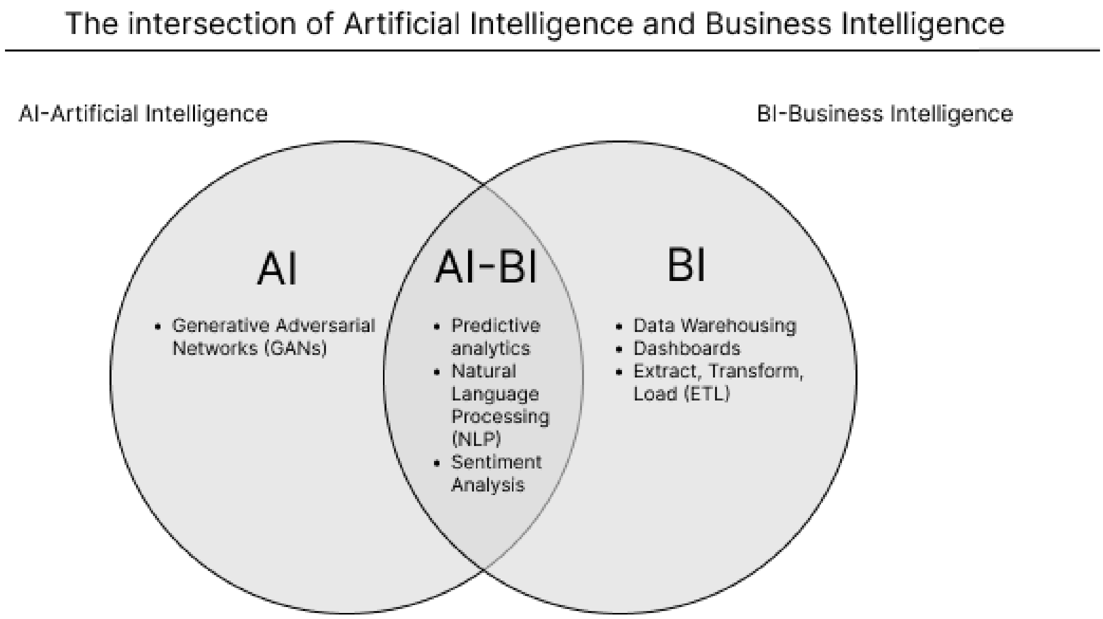


FIGURE 1 The intersection of Artificial Intelligence and Business Intelligence

2 BACKGROUND

In this chapter, we delve into the foundational concepts underpinning our research. The foundational concepts are business intelligence and artificial intelligence. Understanding these concepts is crucial for comprehending their intersection and impact in modern business contexts.

2.1 Business intelligence

Business intelligence can play an important role for organisations. Over time there have been many definitions for business intelligence and it can be easy to feel overwhelmed by the sheer amount of information that is available about Business Intelligence. This literature review aims to present a comprehensive overview of the history of BI and provide clarity regarding the definition of BI.

The first time business intelligence is used is in the Cyclopaedia of Commercial and Business Anecdotes in 1865 by Richard Miller Devens (1868). Business intelligence was used to refer to Sir Henry Furnese, a banker that was able to receive information about market needs and battle outcomes before his competitors Sir Henry Furnese was the first one to receive the outcomes of battles fought. The rapid acquisition of the outcomes of the battles contributed to his financial gains. During that period, computers and technology did not play a significant role, and the phrase "business intelligence" pertained to the possession of valuable business insights. Upon examining the modern definition of business intelligence, it becomes evident that its meaning has undergone significant transformation. Presently, BI is considered to contain both technical and organisational dimensions.

There exist numerous definitions of business intelligence. The history of business intelligence starts in 1958, when an article of Hans Peter Luhn, (1958) was published in IBM journal. In this article he describes a system that is designed to utilise data-processing to auto abstract and auto encode documents.

In addition, creating automatic action points for an organisation. He calls this a business intelligence system.

> *''The objective of the system is to supply suitable information to support specific activities carried out by individuals, groups, departments, divisions, or even larger units.''*(Luhn, 1958)

In 2010 there was conducted research towards understanding business intelligence by Shollo & Kautz (2010). In the research article, 103 articles related to BI in the period of 1990 to 2010 have been analysed. It was constructed that BI is described as a process, a product and a collection of technologies, or a mix of these, which involves data, information, and decision making, as well as related processes, and technologies that support them.

2.1.1 Definition of business intelligence

To fully grasp the scope of business intelligence, it is essential to consider its formal definition. This subsection provides a clear and concise description of business intelligence. Business intelligence can be viewed from both a technical and an organisational perspective. BI consists of a set of methodologies, technologies, processes, and architecture. Combined these components aim to transfer raw data into useful information that can contribute to the achievements of organisational goals and enhance decision making.

The definition for BI that will be used in this thesis is: *''Business intelligence (BI) is a broad category of technologies, applications, and processes for gathering, storing, accessing, and analysing data to help its users make better decisions.''* by Wixom & Watson (2010)

2.2 Artificial intelligence, machine learning & deep learning

In this chapter the difference between machine learning and artificial intelligence and deep learning is shortly described. Artificial intelligence is a research field related to computer science. Artificial intelligence can be seen as an umbrella term that includes machine learning, and deep learning. Artificial intelligence and the subsets machine learning, and deep learning are illustrated in Figure 2.

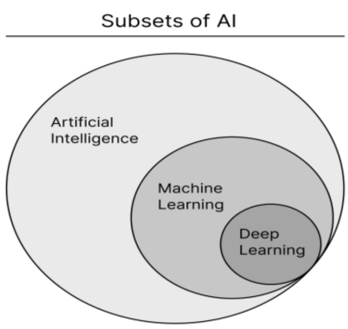


FIGURE 2 The subsets of AI

2.2.1 Artificial intelligence

Artificial intelligence is a rapidly evolving field of computer science. AI involves the development of intelligent machines capable of performing tasks that typically require human intelligence, such as recognizing speech, decision making, and problem solving. The goal of AI is to create machines that can operate autonomously and adapt to changing environments. AI has emerged as a sphere of strategic importance with potential to be a key driver of economic development. AI also possesses considerable societal implications (Samoili et al., 2020). Despite the increased interest in AI by the academia, industry and public institutions, there is yet to be established a standard definition of what AI actually involves (Samoili et al., 2020). Since measuring human intelligence is a complex task and its definition is subjective, various attempts have been made to quantify it (Gardner, 2011). The objective definition of something as subjective and abstract as intelligence has falsely led to an impression that a well-defined definition cannot be achieved. As a result, definitions found in literature, policies, and market reports are vague and focus on the ideal rather than a measurable research concept.

The research of the European commission has identified the following common features in AI definitions (Samoili et al., 2020):

- Environmental awareness: recognizing and understanding the complexities of real-world environments.
- Information processing: gathering and analysing input data.
- Decision making (including reasoning and learning): with a certain level of autonomy making informed decisions and performing tasks, which includes adapting and responding to environmental changes.
- Achievement of specific goals: the primary purpose of AI systems is to successfully achieve predefined objectives.

The European Commission has designated the High-Level Expert Group (HLEG) on Artificial Intelligence to primarily assist in executing the European AI Strategy. The HLEG has created a concrete definition to create a starting point for the development of the operational definition. The AI definition is based on the review of 55 relevant documents covering institutional reports, and AI policy, research publications and market reports. HLEG definition of AI is: *"Artificial intelligence (AI) systems are software (and possibly also hardware) systems designed by humans (2) that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions."* (Samoili et al., 2020). The European commission in addition to creating the definition of AI also funded research to create a taxonomy and keywords of AI for mapping purposes. The taxonomy and keywords can be found in Appendix II.

2.2.2 Machine learning

Machine learning is a subset of AI. In the research of Kühl et al., (2019) it is explained how machine learning contributes to artificial intelligence. Machine learning is what the name describes it, it involves machines to learn from data. Machine learning models are able to use statistical algorithms to learn patterns from the input data and make predictions or decisions based on the patterns. Nowadays machine learning is increasingly used in business intelligence. Machine learning is used to help to understand complex systems and automate decision making. Machine learning is especially used to solve complex problems. There are three forms of machine learning: (1) Supervised learning (2) Unsupervised learning (3) Reinforcement learning. For (1) supervised learning there is a labelled dataset to train the neural network. (2) Unsupervised learning hereby the neural network is given a raw dataset where the data is not labelled to train the neural network. (3) Reinforcement learning hereby there is a feedback loop installed where the neural network is able to learn from past experiences. There are two types of reinforcement learning: Positive reinforcement learning & negative reinforcement learning. Machine learning is closer related to BI than AI. BI aims to extract knowledge from data which is exactly what machine learning is doing. To show how much machine learning contributes to BI we can look at the applications of machine learning that influence BI. Prior to 1985 commercial applications of machine learning were virtually non-existent (Reshi & Khan, 2014). Nowadays the applications of machine learning are: speech recognition, computer vision, bio-surveillance, robot control, accelerating empirical sciences.

The adoption of machine learning technologies for better business intelligence is expected to grow exponentially in the coming years. The machine learning market share is expected to reach 106.52 billion by 2030 with a compound annual growth rate (CAGR) of 38.76% (Shubham, 2020). Furthermore in the top data and analytics trends of Gartner AI is mentioned (Panetta, 2021). Another case of machine learning contributing to BI is the new use of sentiment analysis using machine learning for business intelligence (Chaturvedi et al., 2017). It suggests the use of sentiment analysis classification can be an effective method for examining textual data from different sources.

2.2.3 Deep learning

Deep learning is a subset of machine learning that involves building artificial neural networks with multiple layers (three or more) to analyse and learn from large datasets. The term "deep" refers to the depth of the network, which is characterised by a large number of layers that enable the network to extract high-level features and patterns from complex data. These artificial neural networks attempt to simulate the behaviour of the human brain. (IBM, n.d.) The multiple layers can be seen in feedforward neural networks (FNN) if the FNN contain multiple hidden layers they are considered deep feedforward networks, a feedforward neural network with many hidden layers falls under the umbrella of deep learning. On the other hand, feedforward neural networks with only a single hidden layer are typically considered as part of traditional machine learning. Feedforward neural networks are rising in popularity and the feedforward neural network are used to accurately solve complex nonlinear problems (W. A. Khan et al., 2020). Feedforward neural networks are applied in pattern classification/recognition, system modelling and identification, signal processing, image processing, control systems and stock market predictions (Sazli, 2006). The complex nonlinear problems are harder to solve using classical statistical techniques than with feedforward neural networks (Tkáč & Verner, 2016; Tu, 1996).

Typically, the architecture of machine learning is less complex than that of a deep learning model. Machine learning algorithms are designed to work with structured data, which can be represented in a tabular format. The algorithms use mathematical techniques such as linear regression, decision trees, and random forests to model relationships between input variables and outputs. Machine learning can for example also categorise data. For example, suppose we have a collection of photographs depicting various pets, and our aim is to classify them into categories like *''horse''*, *''bear''*, *''bunny''*, etc. Deep learning can determine which features (e.g. eyes, nose) are the most important for differentiating each animal. In machine learning, this hierarchical organisation of features is required to have manual input from a human expert. By utilising techniques such as gradient descent and backpropagation, the deep learning algorithm refines and adapts itself to enhance accuracy, this enables it to make predictions regarding a new input animal photograph with increased precision (IBM, n.d.).

In contrast to structured data deep learning models are specifically engineered to also be able to process unstructured data, which can take many forms like: Text files, multimedia content, email, spreadsheets, scientific data, mobile communications data, email, audio (MongoDB, n.d.) The fundamental concept of deep learning is to create a neural network architecture that can learn from data. It is particularly useful for tasks that involve large amounts of unstructured data. The use of neural networks with many layers allows deep learning to learn complex features and patterns that are typically imperceptible to human experts.

Training a machine learning model requires the developer to select a set of input features, define a loss function, and optimise the model's parameters to minimise that loss. In supervised learning, the model is trained on labelled data, while in unsupervised learning, the model is trained on unlabelled data to discover hidden patterns. Training a deep learning model is more complex and time-consuming than training a machine learning model. Deep learning models often require vast amounts of data, as well as significant computational resources, in order to achieve quality results.

Deep learning algorithms are incredibly complex, with various types of neural networks tailored to address specific issues or datasets. For instance: Convolutional neural networks (CNNs), Recurrent neural networks (RNNs), and Feed forward neural networks. Numerous deep learning applications employ the use of feedforward neural network architectures (LeCun et al., 2015).

2.3 The intersection of AI and BI

Artificial intelligence and business intelligence have individually contributed and transformed many facets of the modern business world. However, when combined, they become especially powerful. Together they are able to revolutionize the decision-making process and business strategies. In this chapter, we explore the intersection of AI & BI, discussing the significance, benefits, challenges, and the future potential it holds. In the modern digital landscape, data is continuously growing. There are two types of data: structured data and unstructured data. Traditional BI tools need structured data for analysis and are not able to handle unstructured data. This is a problem as 80 to 90% of all collected data is unstructured (Dwight, 2019; Kong, 2019). Consequently, this leaves a large amount of data unused. The research by Solomon, (2004) emphasises the importance of handling unstructured data and the necessity for BI to create and develop BI tools for its collection, integration, cleaning, exploration examination and distribution.

This is precisely where machine learning, a subset of AI comes to the forefront. As databases expand and data becomes more complex, traditional BI tools often fall short or require extensive computational time. Machine learning and deep learning can offer a solution here. By extracting value from unstructured data, organisations can be more productive, make better decisions, understand market conditions, etc. For instance, consider a retail organization using conventional BI tools to analyse sales data. While they can pinpoint the best-selling product of the past month, introducing AI could forecast potential best sellers for the upcoming months. This integration not only provides insights into past trends but also aids in predicting future ones, ensuring optimal inventory management. This study conducts a systematic mapping to explore the intersection between AI and BI. Figure 3 illustrates how, with the help of machine learning and deep learning, unstructured and structured data are transformed into business intelligence, enabling insightful decision-making.

Some benefits of merging AI with BI include predictive analysis, automated decision-making, the ability to handle big data, and uncovering patterns not visible to traditional BI. One of the challenges in integrating AI with BI is ensuring data quality, as AI algorithms require high-quality data to make accurate predictions. This challenge might be mitigated by preprocessing the data. The costs of the initial setup and maintenance of the technology might be high. However, the innovation of cloud BI made BI affordable for many companies.

The evolution of AI and BI integration is expected to accelerate. At the moment systems need time for complex computations however we may soon see AI-BI solutions be able to make real-time business decision on complex problems with shifting variables. The integration of AI into BI is expected to not only improve but also make modern business decisions more efficient. As illustrated in Figure 1, numerous intersections exist between AI and BI, with applications ranging from predictive analysis and Natural Language Processing (NLP) to sentiment analysis. This intersection promises a vibrant research avenue with extensive benefits for organizations and society at large.

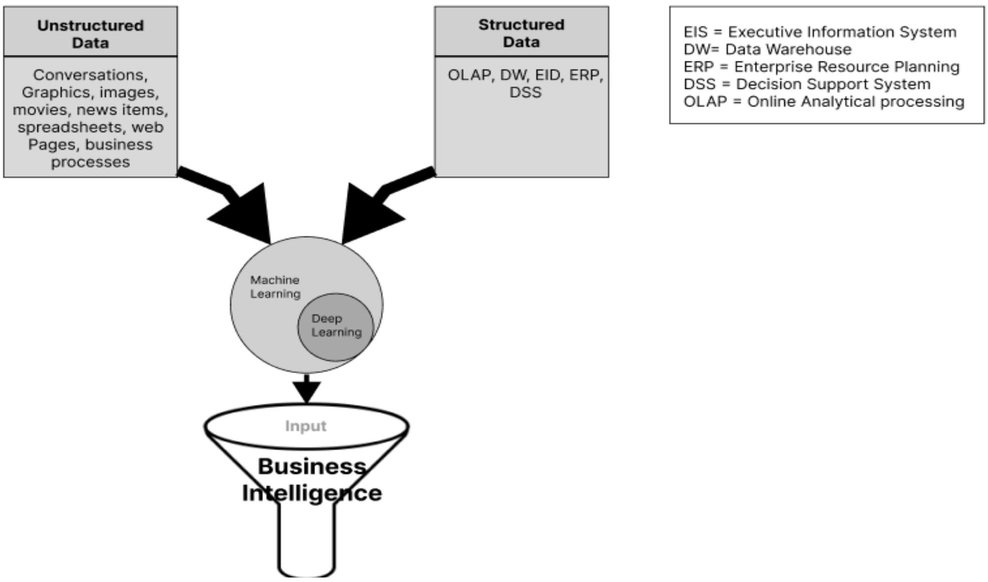


FIGURE 3 Illustrates the transformation of unstructured and structured data into business intelligence through the utilization of machine learning and deep learning techniques

3 CONDUCTING LITERATURE MAPPING

3.1 Research Questions

The purpose of this study is to identify evidence related to Artificial Intelligence and Business Intelligence. The objectives of this study are: (1) classify the existing research work in AI-BI (2) identify key challenges and limitations (3) identify success factors and best practices. The main question is:

What is the current state of research regarding the intersection of the research fields AI-BI?

This study aims to provide a comprehensive understanding/overview of the existing research landscape, research trends, and identification of potential areas of future exploration in the domain of AI and BI. The research questions align with the typical outcomes of systematic mapping studies in software engineering as defined by Petersen (2008). By addressing these research questions, this study aims to contribute and enhance the understanding and knowledge of the intersection between artificial intelligence and business intelligence. Consequently, the objectives lead to two types of research questions. The first four research questions (RQ) are closely related to typical outcomes of the systematic mapping process in software engineering as defined by Petersen (2008) by mapping the main studies on the theme, research approach, publication flora, and publication years. RQ 5 and 6 are related to objectives 2 and 3.

Research questions:

RQ1: In which fora is AI-BI research published?
RQ2: What type of research are mainly employed in the publications within the AI-BI research field?
RQ3: Which work fields or industries are primarily addressed in the literature concerning AI-BI?
RQ4: What are the major research topics, and subdomains, within the field of AI-BI?
RQ5: What are the key challenges and limitations identified in the literature concerning the implementation of AI-BI applications?
RQ6: What are the success factors and best practices identified in the literature for implementing AI-BI solutions?

3.2 Method choice and design

This chapter will give insight into the method choice for this study, followed by an introduction of the method. When a field of research matures the number of research articles in the form of research articles and reports often increase sharply. In this case it is important to summarise and provide an overview. Although AI-BI is relatively new research field, it is maturing rapidly. When we look at the amount of research articles published on the topic AI-BI in the last decade, there has been a steep increase. This thesis aims to contribute to the maturation of the AI-BI research field and help identify research gaps and provide an overview of the research area.

As a thesis topic, conducting a systematic mapping study within the intersection of AI and BI offers several benefits. While AI and BI are different fields, they have an overlap and complement each other. As has been discussed in the introduction AI and BI are increasingly popular research topics and there are many new innovations over the last decade. Since there have been many new publications it can be argued that the research field could benefit from a mapping study. Systematic literature mapping is a secondary study method (Petersen et al., 2008). The goal of executing a systematic literature map is to provide an overview of the research area, identifying the type of research conducted, the found results and the quantity of research. In addition systematic literature mapping can help identify research gaps, and map the frequencies of publications to see the trends over time (Taipalus, 2023).

By conducting a systematic mapping study, it enables researchers to gain insights into how AI is applied to enhance data analysis, decision-making, and predictive capabilities within the field of BI. A systematic mapping study provides a comprehensive overview of the existing literature enabling researchers to identify current research topics. In addition, a systematic mapping study is conceivably able to identify research gaps and research topics that could benefit from additional research. By identifying the research topics within the study field, the researchers also have a better idea on how to conduct their own research and which taxonomy to use. An academic entry into the topic may pose a challenge for new researchers due to its complexity. A systematic mapping can also assist resolving this issue. Kitchenham (2010) suggests that researchers entering a new field would benefit from mapping studies in the area.

Equally important by conducting a systematic mapping this study provides an overview of the different industries that are discovered in primary research articles. This can be valuable for industry professionals especially as it provides a way to find existing literature about AI and BI for a specific industry. Moreover, the results of the research map can be used by organisations that are looking to use AI to improve their BI. The map will provide a quick outlining of the research topics that are popular. The organisation can then evaluate which research topic would be suitable for their organisation to possibly implement. The organisations can also identify which research topics are gaining popularity to stay up to date with the technologies being researched and potentially being utilised by their competitors.

At last, by identifying the key challenges and limitations of the implementation of AI-BI applications organisations and researchers can gain a better understanding of the difficulties that need to be faced during the implementation of AI-BI applications. This knowledge may assist organisations in prepare and prevent potential difficulties and improving the chances of a successful implementation. In addition, researchers might use the knowledge of limitations to focus their research on these areas to discover improvements or different approaches to reduce the limitations.

Research design

This chapter will introduce the systematic mapping method. By defining the methodology well it is less likely that the results of the literature are biased (Kitchenham & Charters, 2007). In addition, by describing the process in detail also the reliability of this study is ensured.

The systematic literature mapping methodology of this thesis is based on previously published guidelines from Petersen (2008), which have been later applied to the information systems research field by Taipalus (2023). Both the guidelines of (Petersen (2008) and Taipalus (2023) have been used for the methodology of this thesis. The methodologies have been compared and from both studies the most suitable guidelines have been selected for this thesis. Additionally, there are some minor changes to the guidelines to fit the thesis best. Systematic mapping is commonly used in evidence based medicine, but has rarely been used in software engineering (Petersen et al., 2008). However currently there is a movement towards more evidence based software engineering Kitchenham (2004) has recommended the adoption of evidence-based approach in software engineering. The new approach to software engineering benefits the software engineering field by ensuring the approaches used are backed by evidence. Despite the fact that AI-BI is not directly part of software engineering the close relation to it makes the evidence-based approach a good fit for AI-BI research. There are research articles that utilise systematic mapping in the field of business intelligence and artificial intelligence. For example, in the field of business intelligence Purnomo (2021) has conducted a mapping study, and in the field of AI Mehta (2019) has conducted a mapping study that uses the corresponding guidelines of Petersen (2008). This study has a different scope than the mentioned articles as this study aims to systematically map the intersection of business intelligence and artificial intelligence. A preliminary search has been conducted to detect if similar literature mapping studies have been performed. For the search the following archives have been used: Thesis archive JYX of University of Jyväskylä, Google Scholar, Scopus. No results have been found. The systematic literature mapping studies that were found contains solely the scope of business intelligence, or artificial intelligence. Finally, it was concluded that at the time of conducting this study no similar mappings studies existed.

The systematic mapping process used for this study is displayed in the Figure 4. The systematic mapping process begins with collecting initial research articles, detailed in chapter 3.1, where the selection of databases and search string selection is discussed. Once these articles are gathered, duplicates are removed. The remaining articles are then evaluated based on their title, abstract, and, for those considered for inclusion in the study, their full text. The criteria for their inclusion are outlined in chapter 3.4. Following this initial evaluation, the research process progresses through snowballing, as elaborated in chapter 3.2. Once the primary research articles have been gathered, they are subjected to a classification scheme which is described in chapter 3.5 and 3.6. Finally, the validity, reliability and generalisability are discussed in chapter 3.7.

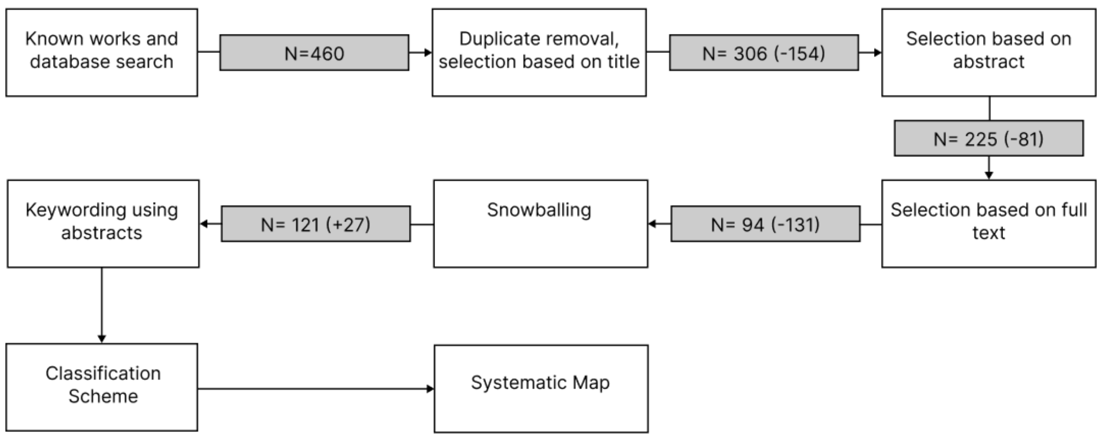


FIGURE 4 Overview of the systematic mapping process used in this study

3.3 Search strategy

In this chapter the search strategy is described. The focus is on the selection of databases, search string, and snowballing. This thesis utilized a search among different databases in the material gathering phase. The selection of appropriate databases to search for primary studies is essential for locating relevant prior research. Some journals focus on a specific field while Google Scholar indexes all research, however it is found that Google Scholar is unsuitable for systematic mappings since the searches yield stochastic results. For example the search *''machine learning AND business intelligence''* returns around 1.640.000 results. This number makes the screening of articles unnecessarily strenuous and renders the search unrepeatable by other researchers. Taipalus (2023) found that it is common to select two to five databases for the search. The publication venues selected for this study, chosen for their relevance to artificial intelligence and business intelligence, include the Association for Information Systems (AIS) eLibrary, the Association for Computing Machinery (ACM), and The Institute of Electrical and Electronics Engineers (IEEE) Xplore. These venues were utilized in the initial search to compile the starting set of articles. In the research article from Taipalus (2023) it is mentioned Association for Information systems (AIS) eLibrary is the most prominent database focused on information systems science. Other common and related databases are Association for Computer Machinery's (ACM), The Institute of Electrical and Electronics Engineers (IEEE) Xplore, and Digital Library. The data collection will focus exclusively on high-ranked journals from these sources.

Search strings

Once the databases have been selected the search string needs to be selected to conduct the initial search on the databases. The initial search has been conducted on 15-6-23. And retrieved 481 research articles, after the removal of duplicates 438 articles were left for the evaluation based on title, abstract, and full text. The search string has been carefully selected after consultation with the supervisor and testing out different search strings to see which gave the best results. The final search strings and results are illustrated in Table 1. In order to get better results with the search terms it was opted to include the AND function which signals that both words need to be included in the search. Because machine learning is a sub domain of AI and closer related to BI than AI the instruction of OR is used which indicates that either word needs to be included in the search.

TABLE 1 Search strings

Database	Search string
AIS eLibrary	Search term (applied to peer-reviewed only): abstract:"business intelligence" AND abstract:"machine learning"OR"artificial intelligence" => 87
ACM	[Abstract: "business intelligence"] AND [[Abstract: "artificial intelligence"] OR [Abstract: "machine learning"]] =>36
IEEExplore	("Abstract":"business intelligence" AND ("artificial intelligence" OR "machine learning")) Filter Journal and conferences => 359

In this thesis, a combination of a broad search strategy and snowballing is employed for data collection. While database searches using specific search strings provide a solid starting point, snowballing ensures comprehensive coverage of key articles in the research field. This method involves tracing references and citations to find additional relevant articles. Wohlin (2014) offers foundational guidelines for snowballing in systematic literature studies within software engineering. For this thesis, manual screening of reference lists was chosen for snowballing. This decision was made because tools like Research Rabbit or Local Citation Network do not disclose their data collection methodologies. Manual snowballing was preferred to ensure thorough checking of all references.

The objective of systematic literature review is to identify all relevant research (Kitchenham & Charters, 2007). However, practice shows that this can be difficult to obtain. Therefore this study opted for the hybrid approach. Wohlin (2022) suggests four hybrid search strategies for identification of primary studies in systematic literature studies. The hybrid approach uses backwards or forwards snowballing. In this study it is opted to take the strategy of taking the original Scopus start set and follow it up with backwards and forwards snowballing in parallel. The backward and forward snowballing is run as two separate processes that both use the same Scopus start set. This strategy enables to retrieve relevant studies. Figure 5 illustrates the amount of articles that were retrieved using forward and backward snowballing.

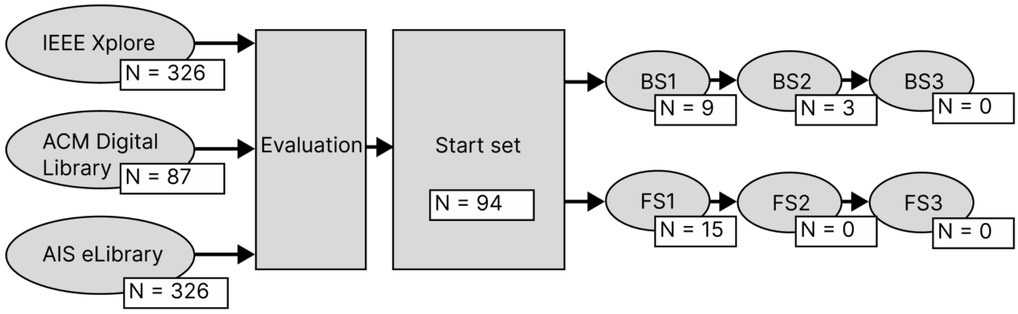


FIGURE 5 Snowballing process with forward (FS) and backward snowballing (BS)

Backward and forward snowballing
In the process of conducting a systematic literature mapping study, the utilization of snowballing techniques more specifically backward and forward snowballing, is important. These techniques play a important role in expanding the scope of the study and contribute to identify and incorporate relevant research articles. In the following section the process of forward and backward snowballing is described in more detail.

Backward snowballing
To establish the foundation of the backward snowballing process a comprehensive Excel sheet is uses. This sheet serves as the initial repository, housing the primary research articles selected for inclusion in this study. The selection has been evaluated based on their title, abstract, and full-text content. For backward snowballing the references of the primary research articles are judged based on the title. If the research article title is found to be out of scope for the study of the systematic mapping study are not added to the excel sheet. If the title is in scope of the study the research article checked for duplicates and then added to the excel sheet and later evaluated based on the abstract and full text. Next the judgement based on the title the research article is also judged based on how and where the article is cited.

Forward snowballing
For forward snowballing the same Excel that holds the primary research articles is used. This sheet serves as foundation for the forward snowballing process.
For forward snowballing the primary research articles are fed into the Google Scholar's search box and the citations are selected. Google Scholar is being used because it provides the most completed list of citations. In the second step of the process the citations are judged based on the title. If the title is in scope of the study the research article is added to the Excel list. Before adding the research article, the article is also judged of the other including criteria for example being a peer-reviewed article. Finally, the selected research articles both by forward and backward snowballing undergo further examination and are evaluated based on the abstract and full text.

3.4 Study selection (inclusion criteria)

In this thesis both inclusion and exclusion criteria are reported. The criteria are chosen based on what serves the process of answering the research questions the best. It is chosen to also report the exclusion criteria as this allows in the screen of articles in the excel document to document on what exclusion criteria the article has been excluded. Articles collected from the database search were subjected to the following inclusion and exclusion criteria.

The including and excluding criteria are applied in three phases: Selection based on title, selection based on abstract, selection based on full text, and snowballing. For the selection based on title in order for an article to be included or considered it should clearly refer to the concepts of artificial intelligence, and or business intelligence. The article could be further examined if a clear decision could not be made by analysing the title. If there are duplicate articles or articles about the same study, only one will be included in the study.
If there can not be made a clear decision if the article should be included based on the title further examination of the abstract is needed. The abstract of the article will be read and there will be made a new decision if the article is to be included in the study. In case there can not be made a clear decision based on the title and abstract the article is to be further examined based on the full text. The evaluation of the full text involves a quick skimming initially. If the initial skimming is not sufficient to determine if the article adheres to the definition of inclusion the text may be fully read.

In order to evaluate if an article is related to business intelligence the definition provided in the introduction is used. This means that an article can also be related to business intelligence even though business intelligence is not named in the article. In order to evaluate if an article is related to AI the definition provided in the introduction is used. In case there is doubt if a article is related to the related to artificial intelligence the article will be evaluated on the use of keywords that are listed in Appendix II. The inclusion of articles will focus on articles that provide insights, discussions, or empirical research related to the application of artificial intelligence techniques in business intelligence or the impact of artificial intelligence on business intelligence processes. If the primary focus of a research article is not on AI and BI. The article will be excluded according to excluding criteria EC6. For example, a study can focus on BI and only briefly mention that AI can be used for BI, but the article does not primarily focus on the AI methods. In this case the article is excluded and EC6 is used for the exclusion categorization. Conversely, if an article is focused on AI but has no relevance to BI, such as a study on AI-generated images, it is also excluded. The searches yielded many articles concerning only BI, these articles were excluded because they are not related to AI. In addition, there were a significant amount of articles that mentioned AI & BI but the primarily focus of the articles is not on BI&AI. These articles were excluded under the excluding criteria EC6.

After the review on abstract 225 articles were included in the research. Because this is a master thesis and the review of 225 articles is a large workload it is decided to apply a filter to the articles included in the study. After analysing the publication years, it was observed that the number of research articles increased significantly after 2013. Consequently, the inclusion criteria were adjusted to consider only articles published in 2013 or later. However, to ensure valuable research published before 2013 is not overlooked, articles with a high citation count are still included in the study. To select these studies, the age of each article is determined, and then the citations per year are calculated, allowing for the inclusion of influential older research. The citation data for the research articles is gathered from Google Scholar. Out of the 57 articles initially included based on their abstracts and published before 2013, 16 were retained after applying a filter of more than 2 citations per year. The remaining 41 articles did not meet this threshold and were excluded according to EC7 criteria.

Including criteria

IC1: High ranked Journal, and/or peer reviewed journal or conference article
IC2: Written in English language
IC3: Published between 2013- 2023
IC4: The article is related to the research field artificial intelligence
IC5: The article is related to the research field business intelligence
IC5: Digital accessible as a student of the University of Jyväskylä

Excluding criteria

EC1: Article is not related to the research field artificial intelligence or business intelligence
EC2: The article is not available in its entirety online
EC3: A duplicate is already included
EC4: Article is not available in English language
EC5: Articles published in editorials, or book chapters
EC6: The primary focus of the article is not on the topic AI&BI
EC7: Published before 2013 and less than 2 citations per year

3.5 Data extraction

Data collection- metadata

The results from the initial search are organized and stored in an Excel spreadsheet. This search yielded 36 articles from the ACM Digital Library, 87 from the AIS eLibrary, and 337 from the IEEE Xplore database. After removing duplicates, a total of 438 research articles remained for evaluation. For each of these articles, the following metadata is collected and recorded: Title, authors, publication year, abstract, keywords, document type, DOI (Digital Object Identifier), number of citations (sourced from Google Scholar), and the originating source database.

Research type

To address research question 2 (RQ2): "What type of research are mainly employed in the publications within the AI-BI research field? ", the classification of research approaches by Wieringa (2006) is employed. This classification, summarized in Table 2, is used to categorize the research approaches of the articles. Wieringa's classification was chosen for its generality and independence from specific focus areas, making it suitable for analyzing a broad range of research within the AI-BI field.

TABLE 2 Research type facet in the research field of AI and BI (adopted from Wieringa (2006) and Petersen (2008)

Research Type Classification	
Category	Description
Validation Research	Validation research investigates techniques that are innovative and have yet to be implemented in practical scenarios. It employs methods such as experiments conducted in controlled settings, aiming to validate the properties and claims of the proposed technique. For example experiments, simulation, mathematical analysis, or prototyping.
Evaluation Research	Evaluation research investigates a problem in (as close as possible) real-world practice or the implementation of a technique. It aims to provide new knowledge about causal relationships among phenomena, or of logical relationships. The research method should support the conclusions statement of the article. In short, an evaluation research provides clarity to a problem, uses correct research methods, and provides new knowledge to the research area. For example, evaluation research in the research area of AI and BI might investigate the practical application and implementations of different techniques within the research field.
Solution Proposal	A solution proposal proposes a solution technique and the relevance is addressed. The proposed technique must be novel or provide substantial improvement of a existing technique. For example, an Solution proposal in the research area of AI and BI might propose a new technique or approach to a existing problem.
Philosophical Papers	A philosophical paper presents a new conceptual framework, general approach, taxonomy, new or adapted research method, or summarization of existing work. Based on the different types of philosophical papers the paper may draw upon existing literature or relies on professional opinions and experiences. For example, this study is a philosophical paper as it summarizes existing work in form of a systematic mapping study in the research area of AI and BI.
Opinion Papers	Opinion papers expresses the opinions of the author or a third party. Commonly no scientific evidence is presented to support the opinion. For example, a opinion paper in the research area of AI and BI might question if the methods that are being used are correct.
Experience Papers	Experience papers describe experience the emphasis is hereby on the *what* and not on the *why*. For example, a researcher or industry practitioner may describe how their AI tool is being used in practice to gain BI.

Industry

Following the initial acceptance of research articles, each article is further evaluated to determine the specific industries or work fields it addresses. This information is extracted by reviewing the abstracts for mentions of relevant industries. If the abstract does not mention an industry, the introduction or conclusion sections may be examined for this purpose. In instances where no specific industry can be identified from the article, this is noted as *''n/a''* (not applicable).

3.6 Keywords (classification scheme)

After narrowing down the articles to the relevant topic criteria, they were thoroughly inspected, and the important keywords were extracted. The keywords were extracted by reading the abstracts and looking for keywords and concepts that represent the contribution of the article. While doing so also the context of the research is identified. These keywords were then combined from different articles into topic categories and sub domains until they could not be merged any further without it becoming too generic and losing too much valuable information. This creates a high-level understanding about the nature and contribution of the research. If abstracts lack the necessary quality to select meaningful keywords, the introduction or conclusion segments of the research article are also studied to select the keywords. Upon establishing the classification scheme, the relevant articles are systematically categorised within the scheme. The classification scheme is fluid and can still change while doing the data extraction, for example by merging and splitting existing categories or adding new categories. In the final document the frequencies of publications in each category can be calculated. In order to form an outline of the results a visualisation in the form of a bubble plot is created. The visualisation makes it straightforward to see for example which categories have been emphasised and which have been neglected by past research. By visualising the results, it is possible to identify the research gaps and identify possibilities for future research.

3.7 Validity, reliability, generalisability, potential biases and research limitations

In this chapter I will discuss the validity, reliability, generalisability of this study. **Validity** is the precision in which the findings accurately reflect the data. In order to secure the validity of the study, there have been selected multiple journals that have excellent published research articles related to the research field. Multiple journals have been selected in order to catch relevant works from multiple publishers. The selecting of a single journal would have posed a risk to the validity of the study. The conclusion validity is threatened by a potential bias of the assessor for the selection of research articles. This will be further discussed in the end of this chapter. **Reliability** is the consistency of the analytical procedures, including accounting for personal and research method biases that may have influenced the findings. In order to ensure the reliability of the study the search for the databases has been limited to one search. The use of one search allows the study to be easily replicated. Furthermore, the method of the study is elaborated in detail which allows the process to be study easily replicated. **Generalisability**

is the transferability of the findings to other settings and applicability in other contexts. In this study the initial articles were collected from the databases: AIS eLibrary, ACM, IEEE Xplore. In order to evaluate the generalisability of the study the question is do these databases cover the global AI-BI research? Because of the time restriction because this is a thesis the search had to be limited to a certain selection of databases. After a discussion with the supervisor the databases have been selected and are determined to cover a significant part of the AI-BI research in combination with snowballing. By excluding the articles that were not available in English. Some articles that might have significant contributions to the AI-BI research field might have been missed. Overall, the study is found to have a strong foundation for generalisability, given the methodical approach of a systematic mapping study, comprehensive database search, and clear criteria.
Addressing **potential biases and limitations:** The efficiency of the initial article collection heavily depends on the chosen search string. If the wrong search term is overlooked or misinterpreted, relevant studies may be excluded. To mitigate the search strings have been discussed and selected in cooperation of the thesis supervisor. Depending on the databases that are used some relevant articles might have been overlooked. This limitation is mitigated by using forward and backward snowballing. This method is used to collect relevant articles that were not included in the initial search. Another limitation might be that terms are overlooked or misinterpreted in the evaluation face of the collected studies. In order to mitigate this limitation. When in doubt if an article should be included the article was proceeded to the next step of the evaluation of articles for example if there was doubt if the article should be included based on the title, the article was further evaluated based on the abstract. This strategy led to numerous articles being excluded when reading the full text. The process of including or excluding studies based on title, abstract, and full-text reading might introduce a selection bias. Especially since the selection is only executed by one person. Because this is a master thesis it was not feasible to have another person overseeing the selection. This bias was addressed by establishing clear inclusion and exclusion criteria. Nevertheless, the subjective nature of interpreting these criteria leaves room for potential bias in this systematic mapping study. Furthermore, this subjectivity might impact the study's reliability, as different researchers could select varying articles if they were to replicate the study. The decision to include only the articles published between 2013-2023 might exclude important articles. This limitation is mitigated by including the research articles before 2013 that received more than 2 citations per year.

4 RESULTS

4.1 Publication fora

Out of the 121 primary studies 30 (25%) were journal articles in 25 different journals. Eighty-eight (73%) studies were published in 85 different conferences, two studies were a workshop of a conference, and one study is a published as a special issue. As can be seen in Table 3 it is clear that the studies included in this mapping study have been published in various journals and conferences. There is no clear journal or conference that stands out with a notably amount of publications on the topic AI-BI. For this reason, searching for AI-BI research should not be limited to a select few journals and conferences. The publications per year are presented in Figure 6. In this figure we clearly see a rise in the number of publications starting from 2015. This is aligned with the literature review where it was found that there is a rising interest in BI and AI. Appendix I lists the primary studies and their corresponding identifiers.

TABLE 3 Number of primary studies published in each forum

Forum name	**Type**	**#**
IEEE Access	Journal	4
Intl. Conference on Management of Data (SIGMOD)	Conference	3
IEEE Transactions on Visualization and Computer Graphics	Journal	2
Industrial Management & Data Systems	Journal	2
Intl. Conference on Computing Communication and Automation (ICCCA)	Conference	2
Multimedia Tools and Applications	Journal	1
ACM Intl. Conference on Pervasive Technologies Related to Assistive Environments (PETRA)	Conference	1
Asia-Pacific Conference on Image Processing, Electronics and Computers (IPEC)	Conference	1
Cognitive Sciences, Genomics and Bioinformatics (CSGB)	Conference	1
Computer Science and Information Technology	Journal	1

Cybernetics & Informatics (K&I)	Conference	1
Economic and Business Aspects of Sustainability	Special Issue	1
Euromicro Conference on Software Engineering and Advanced Applications (SEAA)	Conference	1
European Chemical Bulletin	Journal	1
European Journal of Operational Research	Journal	1
Future Technologies Conference (FTC)	Conference	1
HCT Information Technology Trends (ITT)	Conference	1
IEEE 2nd Intl. Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)	Conference	1
IEEE 43rd Annual Computer Software and Applications Conference (COMPSAC)	Conference	1
IEEE 6th Information Technology,Networking,Electronic and Automation Control Conference (ITNEC)	Conference	1
IEEE 7th Intl. conference for Convergence in Technology (I2CT)	Conference	1
IEEE 8th Intl. Conference on Computing, Engineering and Design (ICCED)	Conference	1
IEEE AFRICON	Conference	1
IEEE II Intl. Conference on Control in Technical Systems (CTS)	Conference	1
IEEE Intl. Conference on Big Data Computing Service and Applications (BigDataService)	Conference	1
IEEE Intl. Conference on Computational Intelligence and Computing Research (ICCIC)	Conference	1
IEEE Intl. Conference on Computer and Information Technology (ICCIT)	Conference	1
IEEE Intl. Conference on Data Mining (ICDM)	Conference	1
IEEE Intl. Conference on Disruptive Technologies for Sustainable Development (NIGERCON)	Conference	1
IEEE Intl. Conference on Power, Control, Signals and Instrumentation Engineering (ICPCSI)	Conference	1
IEEE Pacific Rim Conference on Communications, Computers and Signal Processing (PACRIM)	Conference	1
IEEE Pune Section Intl. Conference (PuneCon)	Conference	1
IEEE Region 10 Conference (TENCON)	Conference	1
IEEE Region 10 Humanitarian Technology Conference (R10-HTC)	Conference	1
IEEE Region 10 Symposium (TENSYMP)	Conference	1
IEEE Sixth Ecuador Technical Chapters Meeting (ETCM)	Conference	1
IEEE Transactions on Mobile Computing	Journal	1
IEEE/ACM Intl. Conference on Advances in Social Networks Analysis and Mining (ASONAM)	Conference	1
IEEE-SEM	Journal	1
Innovations in Intelligent Systems and Applications Conference (ASYU)	Conference	1
Intelligent Automation & Soft Computing	Journal	1
Intl. Conference on Advances in Computing, Communication Control and Networking (ICAC3N)	Conference	1
Intl. Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies (ICAECT)	Conference	1
Intl. Conference on Artificial Intelligence and Advanced Manufacture (AIAM)	Conference	1
Intl. Conference on Artificial Intelligence and Big Data (ICAIBD)	Conference	1
Intl. Conference on Communication, Computing and Internet of Things (IC3IoT)	Conference	1
Intl. Conference on Computational Intelligence and Knowledge Economy (ICCIKE)	Conference	1
Intl. Conference on Computer and Information Technology (ICCIT)	Conference	1
Intl. Conference on Computer Science, Engineering and Applications (ICCSEA)	Conference	1
Intl. Conference on Computing Communication and Networking Technologies (ICCCNT)	Conference	1
Intl. Conference on Computing for Sustainable Global Development (INDIACom)	Conference	1
Intl. Conference on Computing, Communication, Control and Automation (ICCUBEA)	Conference	1
Intl. Conference on Data Mining (DMIN 2015)	Conference	1

Intl. Conference on Digital Data Processing (DDP)	Conference	1
Intl. Conference on Digital Information Management (ICDIM 2013)	Conference	1
Intl. Conference on Edge Computing and Applications (ICECAA)	Conference	1
Intl. Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT)	Conference	1
Intl. Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)	Conference	1
Intl. Conference on Electronics and Sustainable Communication Systems (ICESC)	Conference	1
Intl. Conference on Electronics, Communication and Aerospace Technology (ICECA)	Conference	1
Intl. Conference on Electronics, Computers and Artificial Intelligence (ECAI)	Conference	1
Intl. Conference on Emerging Trends in Computing and Engineering Applications (ETCEA)	Conference	1
Intl. Conference on Emerging Trends in Engineering, Sciences and Technology (ICEEST)	Conference	1
Intl. Conference on Information Technologies and Electrical Engineering (ICITEE)	Conference	1
Intl. Conference on Intelligent Computing and Control Systems (ICCS)	Conference	1
Intl. Conference on Intelligent Computing and Control Systems (ICICCS)	Conference	1
Intl. Conference on Intelligent Engineering and Management (ICIEM)	Conference	1
Intl. Conference on Intelligent Sustainable Systems (ICISS)	Conference	1
Intl. conference on Intelligent User Interfaces (IUI)	Conference	1
Intl. Conference on Inventive Computation Technologies (ICICT)	Conference	1
Intl. Conference on Latest trends in Electrical Engineering and Computing Technologies (INTELLECT)	Conference	1
Intl. Conference on Machine Learning and Computing (ICMLC)	Conference	1
Intl. Conference on Microelectronics, Computing and Communications (MicroCom)	Conference	1
Intl. Conference on Optimization and Applications (ICOA)	Conference	1
Intl. Conference on Orange Technology (ICOT)	Conference	1
Intl. Conference on Quality Management, Transport and Information Security, Information Technologies (IT&QM&IS)	Conference	1
Intl. Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)	Conference	1
Intl. Conference on Security, Pattern Analysis, and Cybernetics (SPAC)	Conference	1
Intl. Conference on Smart and Sustainable Technologies in Energy and Power Sectors (SSTEPS)	Conference	1
Intl. Conference on Smart Structures and Systems (ICSSS)	Conference	1
Intl. Conference on Soft Computing and Measurements (SCM)	Conference	1
Intl. Conference on Software Engineering and Information Management (ICSIM)	Conference	1
Intl. Conference on Trends in Electronics and Informatics (ICOEI)	Conference	1
Intl. Convention on Information, Communication and Electronic Technology (MIPRO)	Conference	1
Intl. Database Engineering & Applications Symposium (IDEAS)	Conference	1
Intl. Interdisciplinary Humanitarian Conference for Sustainability (IIHC)	Conference	1
Intl. Joint Conference on Information, Media and Engineering (IJCIME)	Conference	1
Intl. Journal of Business Intelligence and Data Mining	Journal	1
Intl. Journal of Computer Science and Technology (IJCST)	Journal	1
Intl. Journal of Computing and Artificial Intelligence	Journal	1
Intl. Journal of Information Management Data Insights	Journal	1
Intl. Journal of Theoretical & Computational Physics	Journal	1
Intl. Multi-Conference on: "Organization of Knowledge and Advanced Technologies" (OCTA)	Conference	1
Intl. Symposium on Computational and Business Intelligence	Conference	1
Intl. Symposium on Computational Intelligence and Design	Conference	1
Intl. workshop on Domain driven data mining (DDDM)	Conference/workshop	1

Intl. workshop on Ontology-supported business intelligence (OBI)	Conference	1
Journal of Advances in Information Technolog	Journal	1
Journal of Enterprise Information Management	Journal	1
Journal of independent Studies and Research Computing (JISR-C)	Journal	1
Knowledge-Based Systems	Journal	1
MEC Intl. Conference on Big Data and Smart City (ICBDSC)	Conference	1
MIS Quarterly	Journal	1
Modern Approaches on Material Science (MAMS)	Journal	1
Multimedia Tools and Applications	Journal	1
National and 3rd Intl. Iranian Conference on Biomedical Engineering (ICBME)	Conference	1
Neural Computing and Applications	Journal	1
Open Journal of Applied Sciences	Journal	1
Procedia Computer Science	Conference	1
Product-Focused Software Process Improvement Intl. Conference, PROFES	Conference	1
RoEduNet Conference: Networking in Education and Research (RoEduNet)	Conference	1
The Journal of High Technology Management Research	Journal	1
Workshop on Data Management for End-to-End Machine Learning (DEEM)	Conference/workshop	1
Total		121

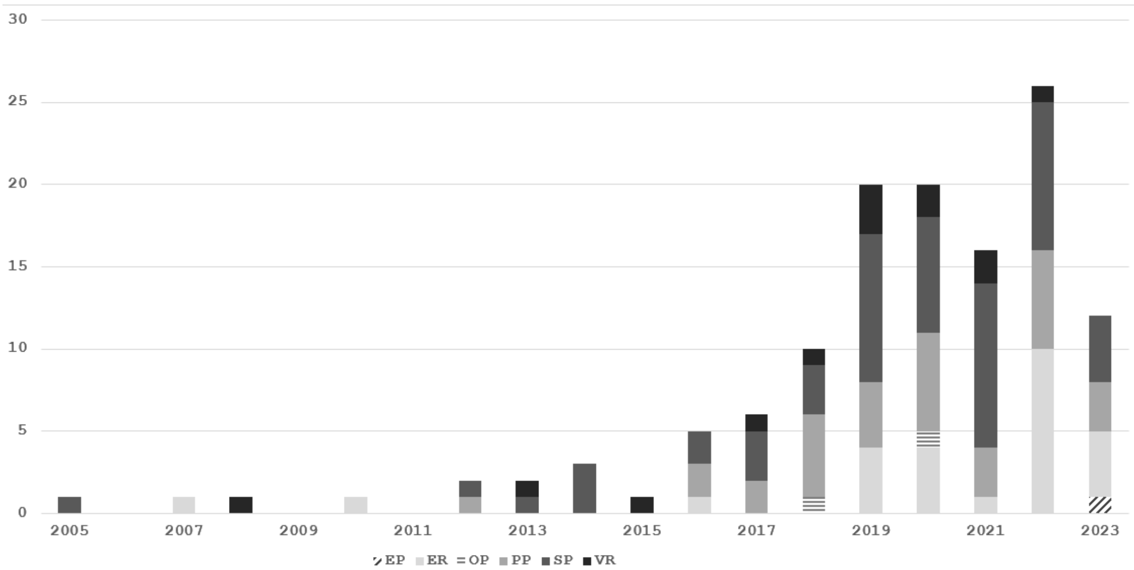


FIGURE 6 Number of publications per year and research type facets: experience paper (EP), evaluation research (ER), opinion paper (OP) philosophical paper (PP), solution proposal (SP), validation research (VR)

The number of citations of the primary studies are presented in Table 4. Because the age of a study has an effect on the number of citations also the citations per year are displayed in Table 4. From the table we can see that there are several research articles that have been highly cited. On the other hand, there are also a significant number of studies that received no citations. While the exact number of citations among primary studies was not documented in this study, the snowballing process revealed that many primary studies had cited each other. This became evident when several studies retrieved through snowballing were later excluded due to being duplicates of already included studies.

4.2 Research themes and approaches

The primary studies are classified according to their topics, which are described in Table 5. Several topics overlap and are related to each other for this reason several studies are candidates to more than one topic. The topics and descriptions are created based on full-text reading of the primary studies and constructed using direct content analysis (Hsiu-Fang, 2005). The primary study distribution between the classification of topics and research type is displayed in a bubble plot in Figure 7.

TABLE 4 Primary studies, number of citations from Google Scholar in Aug. 2023 and citations divided by publication age in full years

ID	citations	citations/y	ID	citations	citations/y	ID	citations	citations/y
PS20	495	45	PS96	11	1,8	PS14	0	0
PS65	300	27,3	PS10	5	1,7	PS15	0	0
PS22	83	20,8	PS54	14	1,6	PS17	0	0
PS57	19	19,0	PS88	6	1,2	PS18	0	0
PS56	49	16,3	PS100	6	1,2	PS21	0	0
PS28	100	14,3	PS116	7	1,2	PS25	0	0
PS27	14	14	PS97	8	1,1	PS31	0	0
PS16	72	12	PS46	1	1	PS35	0	0
PS103	23	11,5	PS47	1	1	PS41	0	0
PS64	102	11,3	PS63	1	1	PS43	0	0
PS83	113	11,3	PS67	1	1	PS45	0	0
PS69	17	8,5	PS70	1	1	PS49	0	0
PS19	50	8,3	PS79	1	1	PS50	0	0
PS120	25	8,3	PS86	3	1	PS51	0	0
PS113	38	7,6	PS89	1	1	PS55	0	0
PS37	21	7	PS107	4	1	PS58	0	0
PS75	28	7	PS39	3	0,8	PS59	0	0
PS101	12	6	PS2	2	0,7	PS60	0	0
PS40	20	5	PS104	2	0,7	PS62	0	0
PS71	10	5	PS7	1	0,5	PS66	0	0
PS85	34	4,9	PS23	2	0,5	PS73	0	0
PS111	22	4,4	PS26	2	0,5	PS74	0	0
PS36	12	4	PS72	1	0,5	PS82	0	0
PS68	19	3,8	PS119	2	0,5	PS84	0	0
PS42	15	3,8	PS34	1	0,3	PS87	0	0
PS81	18	3,6	PS80	1	0,3	PS91	0	0
PS38	52	3,5	PS112	1	0,3	PS92	0	0
PS3	3	3	PS61	2	0,3	PS93	0	0
PS6	15	3	PS8	1	0,3	PS95	0	0
PS29	6	3	PS78	1	0,3	PS98	0	0
PS32	3	3	PS52	2	0,2	PS102	0	0
PS44	9	3	PS90	1	0,2	PS105	0	0
PS30	15	2,5	PS48	1	0,2	PS106	0	0
PS77	5	2,5	PS118	1	0,1	PS108	0	0

PS94	12	2,4	PS1	0	0	PS109	0	0
PS24	34	2,1	PS4	0	0	PS114	0	0
PS33	6	2	PS5	0	0	PS115	0	0
PS53	2	2	PS9	0	0	PS117	0	0
PS76	4	2	PS11	0	0	PS121	0	0
PS99	8	2	PS12	0	0			
PS110	2	2	PS13	0	0			

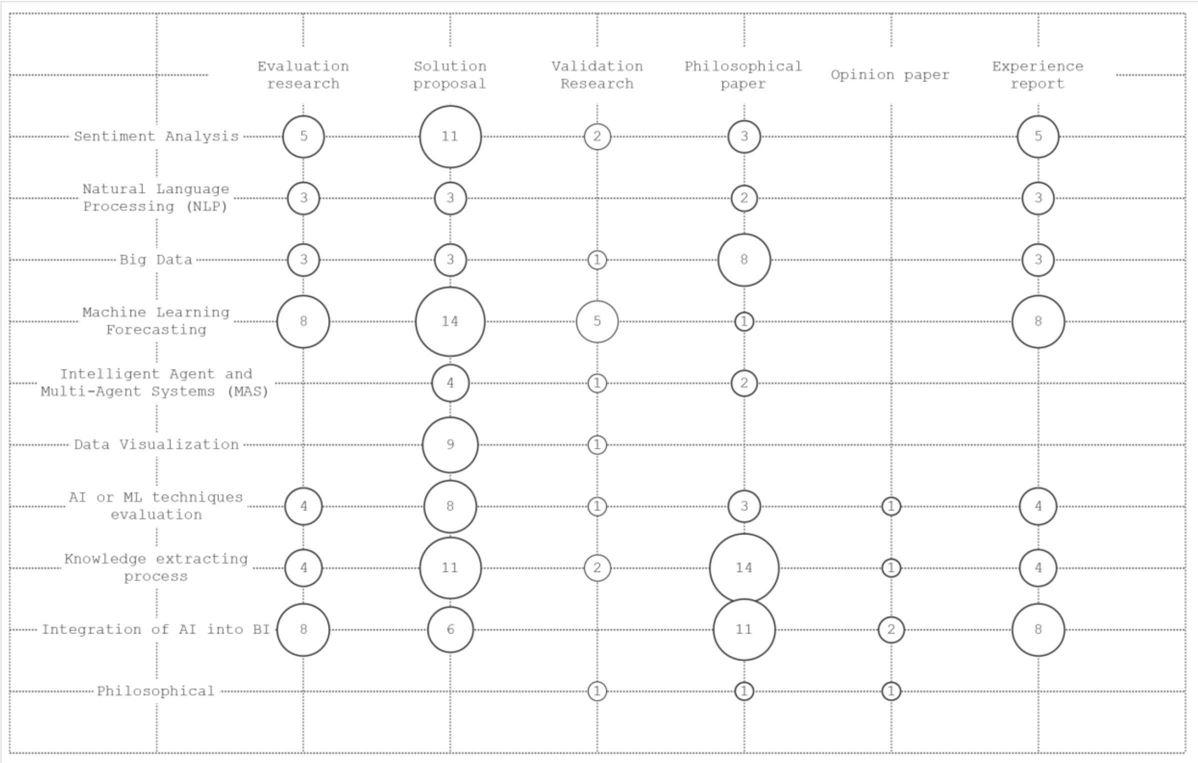


FIGURE 7 Number of primary studies in each research type facet (X-asis) and topic facet (Y-axis) intersection

TABLE 5 Topic description and primary studies categorized according to topics

#	Topic	Topic description	Studies
1	Sentiment Analysis	Sentiment analysis is the process of analyzing digital text to classify the text in positive, negative, or neutral. Sentiment can enhance the decision-making process in the business domain. Sentiment analysis is associated with NLP, classification, big data.	PS2, PS6, PS9, PS19, PS28, PS29, PS31, PS34, PS38, PS57, PS63, PS68, PS70, PS72, PS73, PS79, PS93, PS97, PS98, PS114, PS115
2	Natural Language Processing (NLP)	NLP allows computers to process natural language and understand it in the same way humans do. Studies that are included in this topic are mainly focused on NLP, NLP methods or classification of text.	PS10, PS15, PS16, PS20, PS24, PS25, PS34, PS47
3	Big Data	Big Data refers to large datasets often unstructured. These studies are primarily focused on using business intelligence and artificial intelligence on big data.	PS20, PS29, PS30, PS33, PS48, PS55, PS66, PS77, PS81, PS84, PS85, PS99, PS100, PS107, PS118, PS119
4	Machine Learning Forecasting	Machine learning forecasting is a process that uses algorithms to learn from data and make predictions about future events. These studies are primarily focus on how predictions can be made. Often the focus is on price predictions or customer behavior.	PS11, PS17, PS18, PS21, PS22, PS23, PS32, PS40, PS42, PS43, PS44, PS51, PS53, PS56, PS64, PS68, PS71, PS83, PS86, PS89, PS90, PS91, PS103, PS106, PS108, PS109, PS116, PS117
5	Intelligent Agent and Multi-Agent Systems (MAS)	An intelligent agent is an autonomous entity, that is able to observe an environment using actuators and is able to act upon an environment to achieve a certain goal. A multi-agent system consists of multiple intelligent agents. MAS can be used to solve more complex problems than an individual agent can solve.	PS12, PS22, PS23, PS25, PS55, PS61, PS119
6	Data Visualization	Data visualization is the process of translating data into a visual map or graph. The visualization of data makes it easier to under to understand and gain insights from the data. These studies concern the design or utilization of dashboards and visualization of data. By visualizing data is easier to see patterns, relationships, and trends.	PS1, PS8, PS15, PS27, PS29, PS31, PS44, PS67, PS69, PS88
8	AI or ML techniques evaluation	How to evaluate and measure the performance of AI techniques. To be able to choose the optimal technique. There are different AI techniques these studies evaluate the performance of different AI techniques for a specific application. This is done to be able to choose the optimal technique.	PS24, PS39, PS40, PS45, PS50, PS54, PS56, PS60, PS75, PS78, PS86, PS90, PS91, PS95, PS103, PS111, PS114

9	Knowledge extracting process	Knowledge extraction is the process of extracting knowledge from data. In this case it is specifically concerning the knowledge extraction process using BI and AI. These articles focus on what is needed to be able to extract valuable insights. In order to extract knowledge, they use artificial intelligence and business intelligence. For example, it can be a framework on how to use machine learning in business intelligence solutions. Typically, these articles focus on the holistic approach on how to extract knowledge.	PS4, PS7, PS10, PS13, PS20, PS24, PS26, PS35, PS39, PS46, PS48, PS49, PS52, PS54, PS56, PS58, PS59, PS75, PS80, PS82, PS92, PS94, PS95, PS96, PS99, PS104, PS111, PS112, PS113, PS119, PS121
10	Integration of AI into BI	AI is an upcoming technology and often new applications of AI are explored. AI can be integrated into BI and is known to be a powerful combination as AI can replace some of the traditional BI methods. These studies discuss how AI or ML can be integrated and applied into BI	PS3, PS5, PS13, PS14, PS20, PS24, PS37, PS41, PS44, PS50, PS56, PS58, PS59, PS62, PS65, PS67, PS74, PS77, PS81, PS84, PS87, PS101, PS102, PS105, PS110, PS111, PS112, PS120
11	Philosophical	Philosophical questions relating to artificial intelligence and business intelligence. These studies are asking philosophical questions about artificial intelligence and business intelligence. For example, how will the future look like? Are there any dangers?	PS36, PS76, PS120

4.3 Industries research topics concerning AI and BI

The primary studies in this research are categorized based on the industries addressed in the literature of the accepted articles. Industries that are closely related are merged together during this classification to ensure coherence and relevance in the categorization process. According to the classification scheme which is described in chapter 3.6. It's common for a research article to address multiple industries, resulting in several studies being relevant to more than one industry category. However, studies are not categorized if their scope is too broad or if the article's content is applicable across most industry categories. In case SME is mentioned in the article, the article is categorised as retail and e commerce as often SME operate in this industry. Many research articles were mentioning customer but since this is not related to a specific industry these articles were not categorized.

As mentioned earlier articles can include more than one industry. Out of the total primary studies 121 (100%). Fifty-nine (49%) studies were not categorized within a specific industry. Twenty-five (21%) studies were categorised in the retail and E-commerce industry. E-commerce is considered a form of retail. Retail can be defined as the sale of a product or service to a consumer. The different industries discovered in the primary studies are healthcare, finance, manufacturing, retail and E-commerce, energy and utilities, transport and logistics, social media, education, media and journalism, telecommunications, location tracking, crowdfunding, stock market, marketing, real estate, and game industry. The different industries and their frequency are displayed in Figure 7, Table 6, and Appendix III.

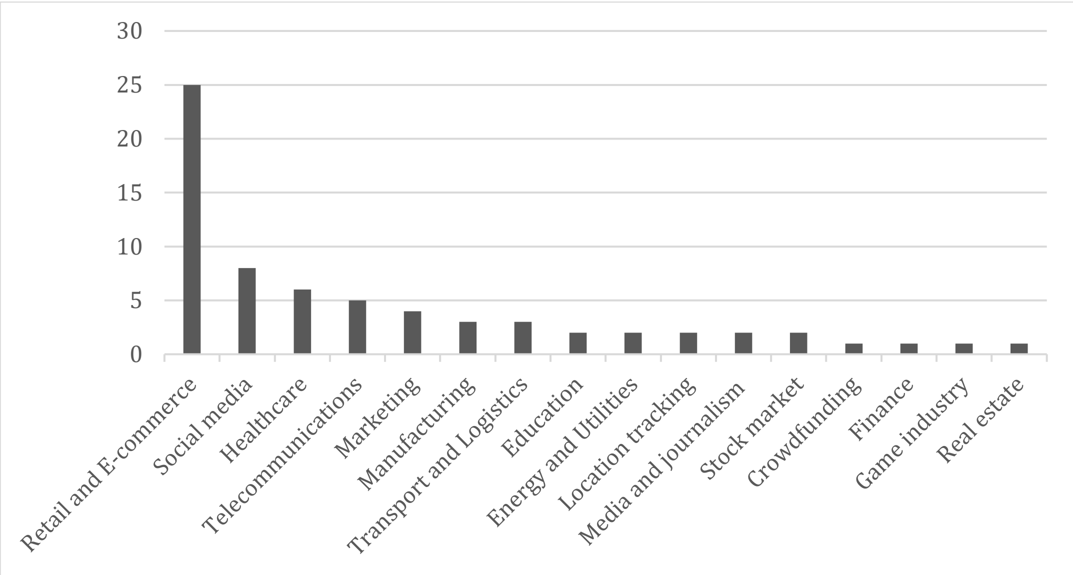


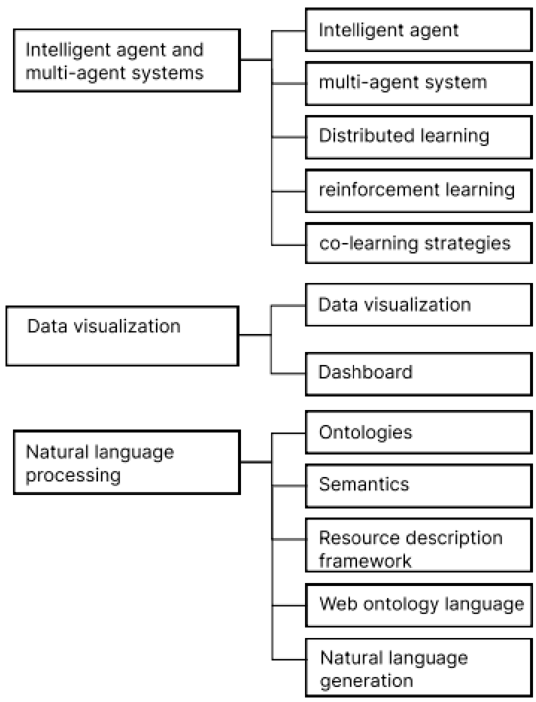
FIGURE 8 Primary studies categorised according to industry

TABLE 6 List of industries and their frequency

Industry	#
Retail and E-commerce	25
Social media	8
Healthcare	6
Telecommunications	5
Marketing	4
Manufacturing	3
Transport and logistics	3
Education	2
Energy and utilities	2
Location tracking	2
Media and journalism	2
Stock market	2
Crowdfunding	1
Finance	1
Game industry	1
Real estate	1
	68

4.4 Common research topics

Beyond the broader concepts and interdisciplinary areas described in Table 5, this study also focuses on specific subtopics and techniques within the fields of artificial intelligence, machine learning, data science, and business intelligence. The focus is hereby on the techniques and methods. The keywords for the accepted papers were generated following the process outlined in chapter 3.6, helping to identify common research topics. These keywords were recorded in the *''categories (keywords)''* column of the Excel file. Through three iterations of this process, a comprehensive taxonomy of categories was developed, offering a structured insight into the study's various research topics. Figure 9 displays the taxonomy of the intersection of artificial intelligence and business intelligence. The taxonomy displays primarily the subdomains, commonly used techniques, and methods within the field of AI-BI.



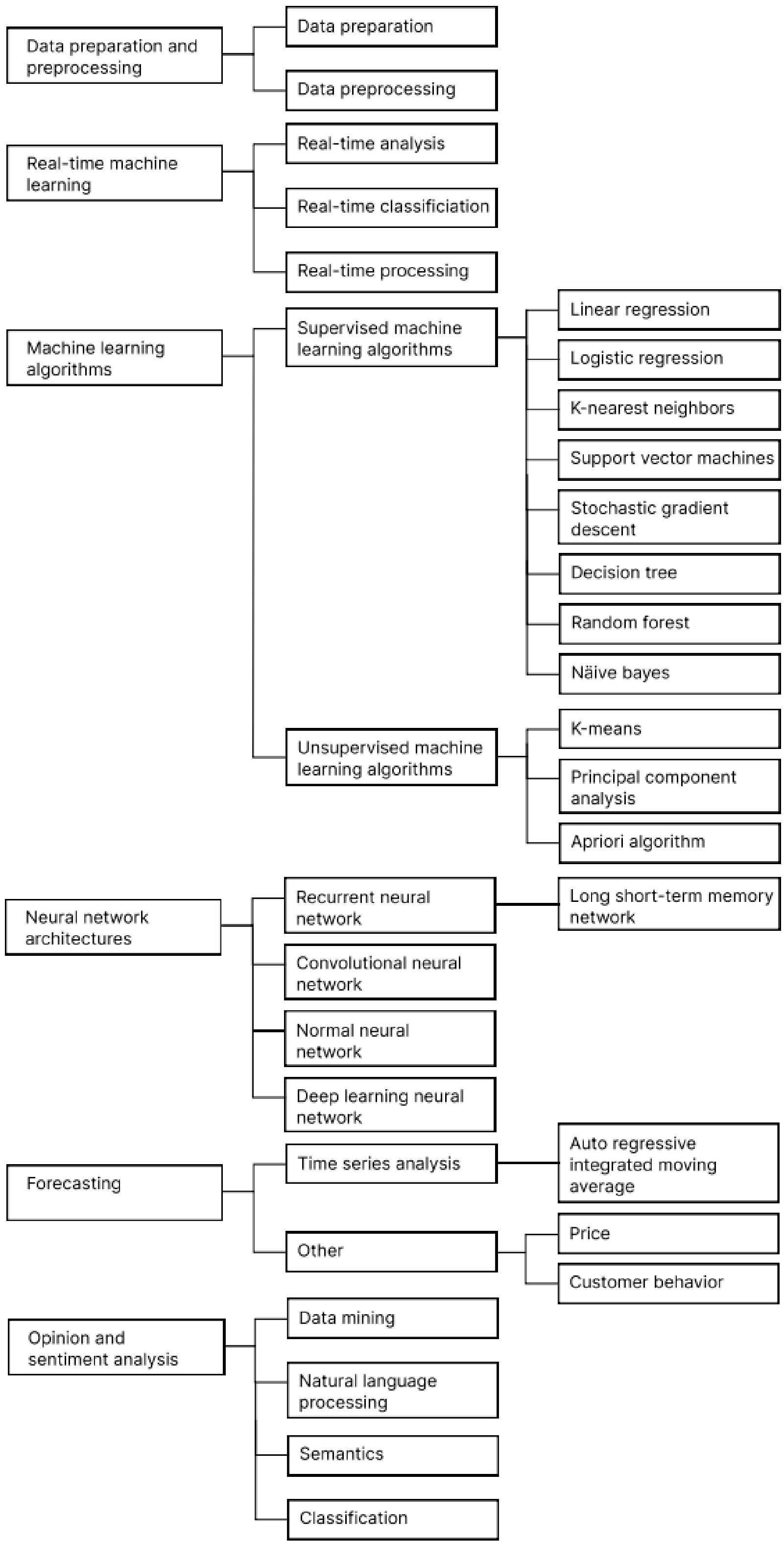


FIGURE 9 Taxonomy of the intersection of artificial intelligence and business intelligence

4.5 Key challenges and limitations of AI and BI

In examining the intersection of AI and BI, it becomes evident that the challenges and limitations are not merely technical but are in addition rooted in strategic and procedural foundations. This chapter synthesizes findings from primary research articles through a methodological approach that combines keyword analysis. The software program ATLAS is used for thorough analysis of the text. The software program allows searches on certain keywords and synonyms. By applying these searches for keywords such as *''limitation''*, and *''challenge''* on the primary studies.

One of the most prevalent challenges highlighted by Figalist (2020) is the tendency of AI in software analytics and business intelligence to remain confined to a prototype stage, with subsequent applications of the technology rarely are used for data-driven decisions. The study identified five interdependent drivers that impeded the utilization of AI and BI systems. An absence of priority, coupled with constraints on time and resources result in a low quality of data and the inability to cross the cultural gap between data scientists and other stakeholders. This leads to an inefficient prototypical analysis and a failure to establish its utility, which in turn prevents an increase of the priority and consequently the allocation of time and resources.

The challenge of maintaining high data quality is echoed by Hamzehi & Hosseini, (2022) who point out the importance of data integrity of repositories. Without optimal data management, the risk of generating inaccurate analytics is increased. This concern coincides with the problem of data cleaning, in particularly the handling of missing values (Afzal, 2023) pointing toward a broader theme and highlighting the fundamental role of data quality in effective implementation of AI and BI systems.

The lack of transparency, another significant challenge cited by Figalist (2020), is reflected in the broader business intelligence context by Schmitt (2023), who illuminates the reasons for limited adoption of deep learning in business intelligence functions. This limitation stems from factors such as computational complexity, the absence of a big-data architecture, the non-transparent nature of deep learning, skill shortages, and the lack of leadership commitment.

Another critical limitation, as identified by Vashisht (2020) is that data is time bound. It is found that by the time data is delivered to executive teams, it's often already outdated, compromising its value for strategic decisions. This problem transcends technical difficulties, casting light on the broader organizational imperative for agility and the integration of real-time data analytics. A theme that resonates through multiple foundational studies (PS2, PS56, PS68, PS80, PS101, PS102, PS118). This highlights the pressing need for a fundamental change toward agile and real-time data analytics.

This synthesis reveals a multi-faceted landscape of challenges that are not only technical but also strategic and organisational. The continuous thread across the literature suggests that for AI-BI systems to reach their full potential, a confluence of technological advancements, clear strategic objectives, and enhanced data governance practices is imperative. Therefore, it is suggested that future research and applications in AI-BI consider these integrated themes, focusing on holistic improvements rather than isolated technical fixes.

4.6 Success factors and best practices

This chapter elaborates on the success factors and best practices identified in the literature related to artificial intelligence and business intelligence. To address the research question *''What are the success factors and best practices in the literature for implementing AI-BI solutions?''* To answer this research question this study systematically analysed the success factors and best practices mentioned in the primary research articles. This process involved an in-depth examination the primary research articles and utilizing the ATLAS software for detailed textual analysis. The use of this software enabled targeted searches using keywords and their synonyms, specifically "*success*", "*best practices*" and "*metrics*" to collect the information related to these keywords.

The gathered data revealed considerable variation in defining success factors across different studies. For instance, one study by Alqhatani (2022) identified the strategic decision making through customer analysis as key success factor. Another study by Gao (2019) investigates the effectiveness of an algorithm, hereby the error squared criterion function E was used as a performance metric in assessing the effectiveness of an algorithm. Similarly Deshpande (2017) employed a popularity metric to evaluate the prediction success of online content. As Figure 7 shows there are numerous research articles the topic *''AI or ML techniques evaluation ''* these articles are dedicated to assessing the effectiveness of different algorithms. Despite the differences in metrics and success factors, a common pattern emerged from the literature: The critical need to define clear project goals and corresponding metrics to effectively evaluate project success. This finding is further supported by Figalist (2020) Who noted that *''one of the key challenges is selecting the right metrics to serve a specific purpose or to reach a specific goal. ''* Desai (2021) further emphasizes this, arguing that goal setting is fundamental to project success, providing benchmarks for evaluation.

Another success factor is highlighted in the study by Vashisht (2020) that calls attention to the significance of the data sets used in model or framework creation. As Vashisht (2020) pointed out, the success of a model is intrinsically linked to the quality of the data set used for the designing, building and training of a neural network. Furthermore, the importance of data quality was underscored by Holm (2019), who observed that while evaluating clustering (an unsupervised machine learning technique) the presence of labelled data is crucial. Evaluations based on unlabelled data can yield varying results, despite generating valid clusters.

In addition to these specific factors, a higher-level insight was gained regarding the selection of algorithms and techniques. A prevalent theme across the studies was that the effectiveness of AI-BI solutions hinges on analysing the environment and objectives to choose suitable algorithms or techniques. Moreover, it's often feasible to empirically test these selections for efficacy. In summary, this chapter has illuminated the diverse yet interconnected factors influencing the successful implementation of AI-BI solutions. These factors, ranging from metric selection and goal definition to data quality and algorithm choice.

5 DISCUSSION

This chapter discusses the study results and compares them with prior research. This chapter will further discuss the implications for the following sub sections: research, industry, and education. In addition, the success factors, best practices, and limitations are discussed.

5.1 Implications for research

This chapter delves into the implications of this study on research within AI and BI domain. The initial literature review and results collectively depict a diversely spread AI-BI research landscape, with no dominant journals or conferences as can be interpreted in Table 3. This dispersion signals both an interdisciplinary richness and a lack of central, unified, or authoritative sources. The fragmented nature could suggest the field is still in an exploratory phase, dealing with a vast array of methods, applications, and theories without a converging consensus or clear-cut dominant methodologies.

A noteworthy pattern, underlined by the initial literature review and the results in Figure 6, is the increasing interest in AI-BI from 2015 onwards. This growing trend resonates with the broader technological advancements and the infusion of AI in various business intelligence applications. Especially the topics sentiment analysis, knowledge extracting process, machine learning forecasting, and integration of AI into BI gained significant traction. This aligns with the findings of the initial literature review where it indicated that data is growing and AI capabilities in processing large datasets, and understanding human language, and predictive analytics are changing the BI solutions.

The research field of AI and BI is an evolving and dynamic field with rapid advancements, methodological diversity, and pressing challenges. This statement is supported by the results in Figure 7 as it shows a high amount of solution proposal research articles which indicates novel solutions or substantial improvements to existing ones. With the large amount of 121 research articles related to both AI and BI it's clear that AI has potential to make BI better, but it is important to look carefully and realistically at how these technologies are used and the challenges they face.

The wide array of methodologies and approaches encountered in the research articles, as well as the diversity of topics, may indicate a vibrant, explorative research field. However, this could also signify a lack of depth in certain areas, with research spreading thin across too many disparate themes. This raises questions about the depth of understanding and advancement in specific AI-BI domains. Given the extensive range of topics and methods, there's an implicit imperative for more standardized, and validated approaches in AI-BI research. The diversity is certainly enriching, but it also calls for a more unified framework or benchmarks to validate various AI applications in BI contexts.

The combination of the diversity of topics and the limitation that AI and BI solutions might stagnate in the prototype stage (which is discussed in chapter 4.5) root the need for practical, workable solutions that can be used on large scale. This will help move the ideas from just theory to useful tools in the business world. Practical workable solutions ensure the benefits of AI and BI can be experienced across various industries. This widespread applicability helps in maximizing the positive impacts of these technologies. Although it can be useful to have workable large-scale AI-BI solutions that can be applied in various industries it can be argued it potentially is difficult to achieve considering the industries have different characteristics and there might not be a one solution fits all.

What is interesting to note is that some of the findings in the initial literature review do not align with the results of the study. For example, in the initial literature review several applications of machine learning application like computer vision, speech recognition, bio surveillance, robot control. However, these applications are not mentioned or very limited mentioned in the primary research articles. Nevertheless, the terms deep learning, feedforward neural networks, convolutional neural networks do align with the findings of this study as the terms can be found in the keywords illustrated in Figure 9. In short, the findings reveal a fragmented yet evolving AI and BI research landscape, lacking dominant methodologies but enriched by a diversity of approaches since 2015.

The key focus areas like sentiment analysis and AI integration in BI reflect a shift towards practical applications of AI in processing complex data sets. However, the disparity between the initial literature review and study findings suggests potential gaps in current research. The need for standardized, scalable solutions is evident to transition from theoretical exploration to impactful business tools, highlighting the importance of a more cohesive approach in AI-BI research. Chapter 5.4 will touch upon how this cohesive approach can be achieved.

5.2 Implications for industry

This chapter delves into the implications of the results for the industry. Chapter 4.3 offers a comprehensive look at how artificial intelligence and business intelligence are currently being integrated and studied in various industries. With an understanding of these applications and trends, we can extrapolate potential implications and future directions for these industries. This chapter will explore these implications, focusing on how businesses might utilize the insights from the primary studies to innovate, optimize, and remain competitive. This is valuable information as indicated in the introduction companies that adopt BI can gain a competitive edge (Marilex et al., 2018).

AI and BI technologies are becoming increasingly more essential in driving business decisions, enhancing operational efficiency, and understanding customer preferences across multiple sectors. However, given the diversity in application and context, the specific implications for each industry may vary. Despite this, several overarching themes emerge. Across all industries, the importance of data-driven strategies is paramount. As utilizing AI and BI for predictive analytics, market trend analysis, and consumer behaviour insights can guide more informed decision-making (Chen et al., 2019; M. A. Khan et al., 2020; Lin et al., 2019; Mahoto et al., 2021; Zhang et al., 2023). Especially in retail, e-commerce, social media, and telecommunications, AI can help in personalizing customer interactions, improving customer satisfaction and loyalty (Bharadiya, 2023b; Xiao et al., 2022). In sectors like manufacturing, transport and logistics, and energy and utilities, AI and BI can significantly optimize operations, reducing costs and improving service delivery (Bellini et al., 2021; Bramer et al., n.d.; Wang et al., 2022).

Given that 21% of the studies focused on retail and e-commerce, the implications in these sectors are significant. Especially since the retail and ecommerce industry is a large industry and growing every year. The retail and ecommerce industry is estimate to grow from 4.96 billion USD in 2021 to 11.6 billion USD by 2030 (Straits Research, 2022). AI can revolutionize inventory management, supply chain optimization, and personalized shopping experiences. Retailers can also leverage AI for price optimization, predicting market trends, and customer service automation like chatbots (Chen et al., 2019; Chhabria & Damle, 2022; Mahoto et al., 2021).

Furthermore, this study maps out the keywords related to AI and BI. The industry can use the keywords to educate employees or to hire new employees that are already knowledgeable in these topics. Opinion and sentiment analysis is closely related to the industry retail and ecommerce and social media. For this reason, it is an important topic. For industries like retail and ecommerce and social media it recommended to get familiar with opinion and sentiment analysis if they are not already.

The implications of AI and BI in health care consists of AI's role in predictive diagnostics (Hamzehi & Hosseini, 2022; Rasool et al., 2020), patient monitoring (Safari et al., 2018), patient care personalization (Mehta et al., 2019; Ramesh et al., 2016), sales prediction of pharmaceutical products (Dutta et al., 2022), and managing healthcare systems offers substantial benefits (Ramesh et al., 2016). Integration of AI and BI can also aid in operational efficiencies and in dealing with large volumes of patient data (Mehta et al., 2019; Ramesh et al., 2016). For manufacturing though only a small percentage of studies focused on this sector, the implications are profound. AI can contribute to predictive maintenance, quality control, and optimizing production lines. (Bellini et al., 2021; T et al., 2018). Furthermore, in the finance sector the implementation of AI and BI could revolutionize fraud detection (Mohd & Nohuddin, 2021), algorithmic trading (Leung et al., 2014; Yasir et al., 2021), and personalized banking services (Calle-Sarmiento et al., 2022). BI tools can enhance risk management and customer insight analytics.

The integration of AI and BI across various industries presents numerous opportunities for innovation and growth. By understanding industry-specific needs and challenges, businesses can leverage these technologies to gain a competitive edge, improve operational efficiency, and enhance customer engagement. The future of AI and BI in industry looks promising but requires careful consideration of technical, and operational aspects per industry to achieve sustainable and effective integration. As AI and BI becomes more prevalent, there is a growing need for industry professionals skilled in these areas. This highlights the importance of education and training in these fields. Chapter 5.4 will propose a solution for this growing need.

5.3 Implications for education

This chapter gives insight to the findings of this study on education. As described in chapter 5.2 industries can reap the benefits of AI and BI by educating their employees. This chapter will illuminate how this can be achieved.

Based on the keywords illustrated in Figure 9 and Appendix II. It is possible to design a curriculum. The program should be dynamic, and people need to be appointed to monitor new research articles to keep continuously updated in the fast-evolving field of AI and BI. The graduates of the program are proficient in applying AI and BI and can specialize in certain industries.

Hereby a suggestion for the course title: The use of artificial intelligence in business intelligence. And recommendations for the course objective: equip students with a comprehensive understanding of the use of artificial intelligence in business intelligence. Topics include machine learning algorithms, forecasting, neural network architectures, opinion and sentiment analysis, natural language processing, intelligent agent and multi-agent systems, data preparation, real-time data processing, data visualization, and the application of these techniques.

5.4 Future research

This chapter synthesizes the findings from the systematic mapping and examines their implications for future research in the AI and BI research landscape. Figures 6 and 7 map out the current state of the research landscape, revealing prevalent themes and gaps via the distribution and frequency of research types across different topics. This analysis is crucial in identifying important intersections of research types and topics.

The examination of individual topics leads to the identification of overarching patterns and gaps, subsequently guiding us towards potential areas for future investigation. Sentiment analysis and experience reports are an important intersection as it shows the application of sentiment analysis in real-world settings. This is crucial for understanding the practical implications and fine-tuning of sentiment analysis tools. Despite the decent amount of experience reports, there appears to be a lack of ''validation research'' and ''opinion papers'' validation research is essential for confirming the efficacy of sentiment analysis methods in controlled environments. The lack of validation research signals a need for future research to establish the efficacy of sentiment analysis methodologies in more controlled settings.

The limited amount of research related to natural language processing (NLP) suggests that this topic could benefit from exploration across all types of research. Although the number of articles is low, it is worth noting that those classified under sentiment analysis often contain NLP research. Given the rapid advancement of large language models (LLMs) like ChatGPT, a significant growth in NLP research is anticipated.

The numerous ''philosophical papers'' within the topic big data may indicate that the field is currently undergoing conceptual and methodological developments or debates. In contrast, the topic machine learning forecasting, which has a lack of ''philosophical papers'' but has a notable number of ''solution proposals''. This indicates ongoing innovation; it could further indicate it is a dynamic field. It can be speculated that the proposed solutions could bear significant economic and societal benefits. For example the research by Rasool (2020) proposes a solution for machine learning to analyse heart disease data. Nevertheless, the scarcity of ''philosophical papers'' on machine learning forecasting signals a need for scholarly discussions on frameworks and potential biases in forecasting models.

Focusing on Intelligent Agent and Multi-Agent Systems (MAS) and Data Visualization, the scarcity of research articles in various categories could be attributed to the specialized nature of these topics. The concentration of 'solution proposal' may suggest a trend towards focused development and application within these fields. It is recommended for future research to focus on the other research types to diversify the research in this area for more comprehensive insights.

The topic evaluation of AI or ML techniques reveals a balance across several categories. Yet there is limited number of ''philosophical papers'' this could indicate there is a need for deeper reflection on the fundamental issues that might not be fully addressed by empirical research alone. For example, philosophical papers can shine light on ethical considerations. As AI/ML systems become more complex, the need for interpretability grows. Philosophical discussions can help in formulating frameworks that can improve the ability to explain the AI/ML applications this is necessary for trust and transparency in AI/ML applications. The argument for the importance of transparency is supported the findings in chapter 4.5 and by the book *''weapons of math destruction''* by O'Neil, (2016). The book gives examples how algorithms can be harmful. And how the secrecy of algorithms can increase inequality and even threatens democracy.

The topic knowledge extracting process exhibits a balanced presence across the different research types. However, the considerable number of ''philosophical papers'' stands out. This hints at the development of new conceptual frameworks and possibly methodological innovations in this area. nonetheless, the limited research article of ''evaluation research'' on this topic suggest a research gap, future research could focus on filling this gap, and in doing so validate the new frameworks and methodologies in real-world settings.

On the topic integration of AI into BI, the strong presence in ''philosophical papers'' and ''experience reports'', indicate a strong theoretical base and conceptual development in integrating AI with BI, which is vital for ensuring that the integration is methodologically sound and robust. In addition to that experience reports offer practical applications of AI in the business context. Similar to the topic knowledge extracting process the shortage of ''evaluation research'' indicates a research gap. Researchers are encouraged to contribute to this topic by validating the integration frameworks and methodologies. In addition to ''validation research'' what might be lacking is ''opinion Papers'' which could provide critical insights and debate regarding the strategic direction and implementation practices of AI in BI contexts.

The examination of individual topics leads to the identification of overarching patterns and gaps. One of the apparent gaps identified is the relative scarcity of validation research. Although there is an abundance of proposed solutions. The relatively fewer validation research papers across domains indicate a gap. There's a rich opportunity for future research to test and validate many of the proposed solutions in real-world scenarios, ensuring their efficacy and robustness. Echoing the findings of W. A. Khan (2020), who emphasize the importance of demonstrating the effectiveness of proposed algorithms in real-world problems or through benchmarking.

Figure 7 shows that solution proposal is the largest discovered research type with 69 research articles. This indicates the research field's orientation towards innovative problem-solving. Solution proposals are mainly new approaches to different problems this would show that the research field is very young. But since there are a decent amount of evaluation research articles this shows that the research area is maturing. However, it is important that these novel ideas into practical application as chapter 4.5 highlighted that AI and BI projects often stagnate in a prototypical stage for this reason it is recommended that future research focusses on validating these novel ideas in practical scenarios.

Philosophical papers are the second largest research type with 45 research articles. Philosophical papers are common in the study, meaning the research articles sketch a new way of looking at the subject, or present a conceptual framework for future research. On shared third place is for experience report and evaluation research with 35 research articles. Opinion papers are the least popular with only 5 research articles. Indicating that the majority of research is data driven. There are only 14 research articles categorized as validation research articles.

Curiously, the ethical dimensions and concerns over data security in AI and BI research seem underrepresented. Given the current ongoing discussions surrounding AI ethics. For example the university of Jyväskylä has been researching a method for implementing ethically aligned AI systems (Vakkuri et al., 2020). Or the research by Balasubramaniam (2020) related to ethical guidelines for solving ethical issues and developing AI systems. However, research specifically focused on the ethical part of AI and BI has been absent in this study. From this we can conclude that there is research focused on the AI ethics however the combination of AI and BI ethics is absent. This finding is unexpected and indicates a significant opportunity for future academic research.

Opinion papers, experience reports, solution proposals and philosophical papers are by nature difficult to replicate. Given that AI-BI is a relatively new research field, it is recommended that future research should focus not only on exploring innovative ideas but also on replicating foundational research articles. Additionally, validating some of the novel innovation ideas would support the maturation of the AI-BI research field.

As illustrated in Figure 6, there is an increasing trend in the number of publications, and it is expected that this upward trajectory will continue. This trend underscores the importance of carefully selecting the research directions for future researchers to focus on. In Table 3 it shows that the research articles are published in various journals and conferences. This makes it difficult for new researchers interested in contributing to the AI-BI research field to find the relevant research articles. In addition, it was found that it was an intense analysis of the studies in order to determine if the articles were related to both AI and BI. For this reason, I would like to propose the idea of creating a distinct name or field label for the intersection of artificial intelligence and business intelligence. Potential names suggestions for the intersection of business intelligence and artificial intelligence are **AI-driven business intelligence (AIBI),** A straightforward name that connects AI to BI. Or **cognitive business intelligence (CBI)** which focuses on the cognitive and intelligent aspects of BI enabled by AI.

For the creation of a distinct name there are pros and cons that need to be considered. A distinct name will help with clarity and recognition by clarifying the focus and purpose of research and academic studies in the area of AI-BI. In addition, it can make it easier for researchers, practitioners, and other interested parties to understand what the field encompasses. This is especially important as the publications related to AI-BI are rapidly increasing as can be seen in Figure 6. A distinct name can further lead to the development of specialized academic programs, courses and research centres dedicated to AI-BI as is suggested in chapter 5.3, these developments can contribute to fostering deeper expertise and knowledge in the field. A distinct name can facilitate collaboration between experts in AI and BI encouraging interdisciplinary research to be conducted and exchange of ideas. The distinct name of the research area of BI-AI is especially applicable for the research articles that focus on high level the integration of AI into BI.

However, there can also be negative effects that need to be considered. For example, the distinct name could potentially narrow the field’s scope potentially excluding valuable contributions from close related disciplines. In addition, the new distinct name may cause confusion as there may still be overlap with other related research fields like: data science, machine learning, and data analytics. This overlap could potentially create confusion about where one field ends, and another begins. Furthermore, while doing research on the background of business intelligence that the definition of business intelligence has undergone significant transformation. And there is no standard definition of business intelligence. This leads us to one further potentially negative effect that fragmentation of research into too many specialized sub fields may make it challenging to establish a unified body of knowledge and common standards. Even though there are negative effect from selecting a distinct name it is found the benefits outweigh the negative effects. For this reason it is recommended to select a distinct name for the intersection of AI and BI.

This chapter aimed to contribute to the understanding of the research field AI-BI. By analysing the findings this thesis mapped out dominant themes and identified key areas for future research. Since there was no prior systematic mapping study on the subject of AI and BI it is not possible to compare the results of this study to prior literature.

6 CONCLUSION

In this thesis, a systematic literature mapping study was conducted for the two research fields artificial intelligence and business intelligence. The goal was to map the current state of research regarding the intersection of the research fields AI and BI. This is an important topic as AI is transforming the conventional BI solutions. The increasing blend of AI into BI systems promises enhanced decision-making, predictive analysis, and improved strategic business developments. Recognizing this, the thesis aimed to shed light on the current academic landscape. The findings have implications on education, research, and industry.

In total 121 research articles were included in the study. It was discovered that the research articles were published in many different journals and conferences. As the initial literature indicated the results show that the number of research articles related to AI and BI are increasing. To be able to define the current state of research regarding the intersection of the research field AI and BI several graphics have been made. By offering an evidence-based perspective on the research field, this study empowers researchers to identify major research topics and areas that have received limited attention. Consequently, researchers can prioritize areas that require further exploration and focus.

The methodological approach of this study consists of both database searches and snowballing. This approach not only facilitated the identification of a wide array of relevant articles but also ensured that the resulting synthesis of literature was as representative as possible. This is critical in a rapidly evolving research area, where new insights are constantly emerging, and the publication landscape is fragmented across various disciplines and fora.

The main findings of this thesis underscore the diversity and richness of the AI-BI domain. This study has highlighted that while there is a clear upward trend in publications, the research is scattered across a different journals and conferences without a central publication venue. This indicates the interdisciplinary nature of AI-BI research and the need for a multidisciplinary approach in future studies.

Moreover, this research has identified key challenges and limitations within the field, such as the necessity for high-quality data to leverage AI algorithms effectively, and the gap between theoretical models and practical applications. It has also surfaced critical success factors and best practices for implementing AI-BI solutions, which are essential for driving the field forward.

The implications of these findings are manifold. For academia, they provide a roadmap for future research endeavours, pointing out the fruitful areas that are ripe for exploration and development. For industry, the insights from this study inform strategic decision-making, particularly in the adoption and implementation of AI-BI systems. For the educational sector, the findings illuminate the need for curricula that are responsive to the changing dynamics of the AI and BI domain, equipping students with the useful skills and knowledge.

In conclusion, this thesis presents a valuable contribution to the body of knowledge in the AI-BI research field. It not only enhances our understanding of the current state of research but also underscores the importance of continued research into this dynamic and impactful area. The implications of this study reach beyond academia, influencing industry practices and educational strategies, thereby highlighting the profound impact of AI and BI on the modern business environment. As we find ourselves in transformative shifts in business intelligence catalysed by AI, this thesis offers a foundation for stakeholders to build upon, ensuring that they remain at the forefront of this evolution.

APPENDIX I LIST OF PRIMARY STUDIES

ID	Publication
PS1	Afzal, U. (2023). NNBI: A Neural Network based Business Intelligence Dashboard for a Clothing Store. Journal of Independent Studies and Research Computing, 21(1), Article 1. https://doi.org/10.31645/JISRC.23.21.1.8
PS2	ALCABNANI, S., OUBEZZA, M., & ELKAFI, J. (2020). A Business Intelligence model to analyze consumer opinions on social networks using machine learning techniques. 2020 IEEE 2nd International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS), 1–6. https://doi.org/10.1109/ICECOCS50124.2020.9314548
PS3	Al-Omoush, R., Fraihat, S., Al-Naymat, G., & Awad, M. (2022). Design and Implementation of Business Intelligence Framework for a Global Online Retail Business. 2022 International Conference on Emerging Trends in Computing and Engineering Applications (ETCEA), 1–6. https://doi.org/10.1109/ETCEA57049.2022.10009688
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PS97	Singh, B., Kushwaha, N., & Vyas, O. P. (2016). An interpretation of sentiment analysis for enrichment of Business Intelligence. 2016 IEEE Region 10 Conference (TENCON), 18–23. https://doi.org/10.1109/TENCON.2016.7847950
PS98	Sreesurya, I., Rathi, H., Jain, P., & Jain, T. K. (2020). Hypex: A Tool for Extracting Business Intelligence from Sentiment Analysis using Enhanced LSTM. Multimedia Tools and Applications, 79(47), 35641–35663. https://doi.org/10.1007/s11042-020-08930-6

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PS100	T, P. K., N, M. T., & Hegadi, R. S. (2018). Literature Review on Big Data Analytics and Demand Modeling in Supply Chain. 2018 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT), 1246–1252. https://doi.org/10.1109/ICEECCOT43722.2018.9001513
PS101	Tamang, M. D., Kumar Shukla, V., Anwar, S., & Punhani, R. (2021). Improving Business Intelligence through Machine Learning Algorithms. 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM), 63–68. https://doi.org/10.1109/ICIEM51511.2021.9445344
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PS103	Thurachon, W., & Kreesuradej, W. (2021). Incremental Association Rule Mining With a Fast Incremental Updating Frequent Pattern Growth Algorithm. IEEE Access, 9, 55726–55741. https://doi.org/10.1109/ACCESS.2021.3071777
PS104	TITU, A. M., & STANCIU, A. (2020). Acquiring businesss intelligence through data science: A practical approach. 2020 12th International Conference on Electronics, Computers and Artificial Intelligence (ECAI), 1–6. https://doi.org/10.1109/ECAI50035.2020.9223190
PS105	Tripathi, M. A., Madhavi, K., Kandi, V. S. P., Nassa, V. K., Mallik, B., & Chakravarthi, M. K. (2023). Machine learning models for evaluating the benefits of business intelligence systems. The Journal of High Technology Management Research, 34(2), 100470. https://doi.org/10.1016/j.hitech.2023.100470
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PS108	Verma, H., & Gochhait, S. (2023). Review and Analysis of usage of Spatio-Temporal Game Analytics. 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS), 1816–1821. https://doi.org/10.1109/ICICCS56967.2023.10142334
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PS113	Wu, M., & Wu, X. (2018). On Big Wisdom. 2018 IEEE International Conference on Data Mining (ICDM), 1–2. https://doi.org/10.1109/ICDM.2018.00009
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PS117	Zhang, D., Zhang, C., & Zheng, C. (2023). Prediction and Analysis of Customer Churn of Automobile Dealers Based on BI. 2023 IEEE 6th Information Technology,Networking,Electronic and Automation Control Conference (ITNEC), 6, 368–372. https://doi.org/10.1109/ITNEC56291.2023.10082554
PS118	Zhang, Y., Ma, H., & Xu, Y. (2013). An Intelligence Gathering System for Business Based on Cloud Computing. 2013 Sixth International Symposium on Computational Intelligence and Design, 1, 201–204. https://doi.org/10.1109/ISCID.2013.57
PS119	Zhao, L. (2019). Business Intelligence Application of Enhanced Learning in Big Data Scenario. 2019 International Joint Conference on Information, Media and Engineering (IJCIME), 149–153. https://doi.org/10.1109/IJCIME49369.2019.00038
PS120	Zohuri, B., & Moghaddam, M. (2020). From Business Intelligence to Artificial Intelligence. Modern Approaches on Material Science, 2. https://doi.org/10.32474/MAMS.2020.02.000137
PS121	Zohuri, B., Moghaddam, M., & Mossavar-Rahmani, F. (2022). Business Resilience System Integrated Artificial Intelligence System. 3, 1–7.

APPENDIX II KEYWORD TAXONOMY

Table 2. Most relevant keywords within each AI domain

AI domain	AI subdomain	Keyword	
Reasoning	**Knowledge representation; Automated reasoning; Common sense reasoning**	case-based reasoning	inductive programming
		causal inference	information theory
		causal models	knowledge representation & reasoning
		common-sense reasoning	latent variable models
		expert system	semantic web
		fuzzy logic	uncertainty in artificial intelligence
		graphical models	
Planning	**Planning and Scheduling; Searching; Optimisation**	bayesian optimisation	hierarchical task network
		constraint satisfaction	metaheuristic optimisation
		evolutionary algorithm	planning graph
		genetic algorithm	stochastic optimisation
		gradient descent	
Learning	**Machine learning**	active learning	feature extraction
		adaptive learning	generative adversarial network
		adversarial machine learning	generative model
		adversarial network	multi-task learning
		anomaly detection	neural network
		artificial neural network	pattern recognition
		automated machine learning	probabilistic learning
		automatic classification	probabilistic model
		automatic recognition	recommender system
		bagging	recurrent neural network
		bayesian modelling	recursive neural network
		boosting	reinforcement learning
		classification	semi-supervised learning
		clustering	statistical learning
		collaborative filtering	statistical relational learning
		content-based filtering	supervised learning
		convolutional neural network	support vector machine
		data mining	transfer learning
		deep learning	unstructured data
		deep neural network	unsupervised learning
		ensemble method	
Communication	**Natural language processing**	chatbot	natural language generation
		computational linguistics	machine translation
		conversation model	question answering
		coreference resolution	sentiment analysis
		information extraction	text classification
		information retrieval	text mining
		natural language understanding	
Perception	**Computer vision**	action recognition	object recognition
		face recognition	recognition technology
		gesture recognition	sensor network
		image processing	visual search
		image retrieval	
	Audio processing	computational auditory scene	sound synthesis
		music information retrieval	speaker identification
		sound description	speech processing
		sound event recognition	speech recognition
		sound source separation	speech synthesis

AI domain	AI subdomain	Keyword	
Integration and Interaction	Multi-agent systems	agent-based modelling	negotiation algorithm
		agreement technologies	network intelligence
		computational economics	q-learning
		game theory	swarm intelligence
		intelligent agent	
	Robotics and Automation	cognitive system	robot system
		control theory	service robot
		human-ai interaction	social robot
		industrial robot	
	Connected and Automated vehicles	autonomous driving	self-driving car
		autonomous system	unmanned vehicle
		autonomous vehicle	
Services	AI Services	ai application	intelligence software
		ai benchmark	intelligent control
		ai competition	intelligent control system
		ai software toolkit	intelligent hardware development
		analytics platform	intelligent software development
		big data	intelligent user interface
		business intelligence	internet of things
		central processing unit	machine learning framework
		computational creativity	machine learning library
		computational neuroscience	machine learning platform
		data analytics	personal assistant
		decision analytics	platform as a service
		decision support	tensor processing unit
		distributed computing	virtual environment
		graphics processing unit	virtual reality
AI Ethics and Philosophy	AI Ethics	accountability	safety
		explainability	security
		fairness	transparency
		privacy	
	Philosophy of AI	artificial general intelligence	weak artificial intelligence
		strong artificial intelligence	narrow artificial intelligence

APPENDIX III PRIMARY STUDY INDUSTRIES

Industry	#	**Research articles**
Retail and E-commerce	25	PS3, PS4, PS6, PS7, PS9, PS21, PS22, PS23, PS25, PS26, PS29 ,PS31 ,PS43 ,PS48 ,PS56 ,PS66 ,PS67 ,PS68 ,PS71 ,PS84 ,PS90 ,PS97 ,PS114 ,PS117
Social media	8	PS9, PS10, PS20, PS24, PS28, PS63, PS65, PS79
Healthcare	6	PS32, PS41, PS81, PS85, PS86, PS88
Telecommunications	5	PS40, PS45, PS78, PS83, PS107
Marketing	4	PS21, PS84, PS90, PS9
Manufacturing	3	PS11, PS67, PS100
Transport and Logistics	3	PS17, PS51, PS67
Education	2	PS12, PS96
Energy and Utilities	2	PS50, PS110
Location tracking	2	PS46, PS52
Media and journalism	2	PS30, PS92
Stockmarket	2	PS64, PS115
Crowdfunding	1	PS60
Finance	1	PS18
Game industry	1	PS108
Real estate	1	PS89
	68	

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