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The Use of Artificial Intelligence in Business Intelligence to Support Data-Driven Decision-Making Using Descriptive Analytics

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ABSTRACT
This study investigates how Business Intelligence (BI) utilises Artificial Intelligence (AI) to support data-driven decision-making using Descriptive Analytics methods. The research reviewed twelve selected articles, identified from an initial pool of 47 articles retrieved from the PubMed, Scopus, and Web of Science databases (2020–2026). A Systematic Literature Review (SLR) approach was employed, in conjunction with the PRISMA protocol, and the methodological quality of the eligible articles was assessed using the Critical Appraisal Skills Programme (CASP) checklist. The results of the review indicate that the integration of AI and BI enhances the efficiency of data analysis, with CRISP-DM-based descriptive analysis reducing data processing time from six hours to thirty minutes. According to the research, Descriptive Analytics is a strategic step towards a Data-Driven Decision Making (DDDM) ecosystem. However, issues such as high costs and labour shortages still need to be addressed.

Keywords—Artificial Intelligence, Business Intelligence, Descriptive Analytics, DDDM, SMEs

1. INTRODUCTION

The digital age has resulted in a significant increase in the volume of data generated daily by both businesses and government entities. The strategic utilization of data through evidence-based approaches has become essential, particularly in the public sector, to enhance policy efficiency [1]. Despite this, many organizations, especially Micro, Small, and Medium Enterprises (MSMEs), continue to rely on intuition rather than fully leveraging data, in part due to limited numeracy skills that hinder effective Data-Driven Decision Making (DDDM) [8]. This challenge is further compounded by the constraints of manual data processing. For instance, Wibowo (2022) reported that analyzing sales data at PT. Telkominfra can require up to six hours when performed manually using Excel, leading to delayed responses and less effective managerial decisions [5].

Integrating Business Intelligence (BI) and Artificial Intelligence (AI) provides a comprehensive solution to these challenges. The combination of BI and AI can accelerate decision-making processes, enhance analytical accuracy, and enable data-driven personalization [4], [6], [11], [13]. For example, a BI system implemented in a multi-entity company achieved a User Acceptance Test (UAT) score of 92%, indicating that a well-designed BI ecosystem can be effectively adopted [2]. Additionally, machine learning techniques such as SMOTE and Random

Over-Sampling for predicting customer churn in the banking sector further illustrate AI's capacity to support data-driven decision-making at the operational level [10]. However, a comparative study and SWOT analysis of AI implementation in Indonesia reveal that adoption remains limited by high implementation costs, a shortage of skilled human resources, and uneven infrastructure across regions [3].

Amid these challenges, Descriptive Analytics emerges as an efficient and low-cost approach to driving data-driven decision-making. The application of Big Data Analytics in business decision-making [9], as well as aspect-based sentiment analysis combined with BI visualization in customer reviews of F&B products [12], demonstrates how a descriptive approach can provide insights into consumer behavior patterns and support strategic business planning. This study comprehensively examines how artificial intelligence within the business intelligence ecosystem can support data-driven decision-making through the Descriptive Analytics approach, with the aim of providing practical insights for businesses currently undergoing digital transformation.

2. LITERATURE REVIEW

2.1 Artificial Intelligence and Business Intelligence

Artificial Intelligence (AI) is a technology that enables computer systems to perform tasks that typically require human intelligence, such as learning from information and recognizing patterns. In a business context, AI has been shown to improve effectiveness in three key areas: Information Management Systems (IMS), the SME sector, and the financial sector [4]. On the other hand, Business Intelligence (BI) is a technology ecosystem that combines data warehouses, ETL, and visualization to facilitate decision-making. When BI is combined with AI and Machine Learning, an organization's analytical capabilities evolve from merely descriptive to predictive and prescriptive, offering opportunities for service personalization and greater operational efficiency—especially for SMEs, which typically face resource constraints [7], [8].

2.2 Data-Driven Decision Making (DDDM) and Big Data Analytics

Data-Driven Decision Making (DDDM) is a decision-making method that prioritizes evidence and data analysis as its primary foundation, rather than relying on personal intuition. The DDDM cycle—which includes data collection, interpretation, and follow-up—not only guides decision-making but also gradually enhances MSME stakeholders' understanding of data, with AI/BI acting as a cognitive accelerator in the process [8]. In a broader context, Big Data Analytics facilitates immediate decision-making and operational efficiency [9]. The implementation of DDDM in the public sector has also been shown to improve accuracy and transparency in strategic planning [1], although the cost of technology and a shortage of skilled human resources remain major barriers to wider adoption.

2.3 Descriptive Analytics Using the CRISP-DM Framework

Descriptive Analytics is a basic level of analytics that answers the question "What has happened?" by collecting statistics, identifying patterns, and presenting historical data. Wibowo et al. (2022) [5] demonstrated its usefulness by applying Exploratory Data Analysis (EDA) based on the CRISP-DM framework to sales data, which successfully reduced analysis time from 6 hours to 30 minutes. This study demonstrates that Descriptive Analytics, although a simple method, holds significant value as a foundation for more advanced analytics and serves as a practical tool applicable to businesses of all sizes.

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3. METHODOLOGY

The Systematic Literature Review (SLR) method is the primary approach in this study because it allows for a systematic, clear, and replicable synthesis of scientific evidence from various relevant literature sources [1]. The SLR method differs from conventional narrative reviews in that it employs a rigorous protocol at every stage of the process—from search and selection to data extraction and synthesis—thereby reducing selection bias and enhancing validity.

3.1 Research Questions

To guide the search strategy, selection process, and synthesis conducted in this study, the following research questions (RQ) were formulated:

1. RQ1: How does the integration of Artificial Intelligence (AI) into Business Intelligence (BI) systems improve the efficiency and accuracy of Descriptive Analytics processes compared to conventional approaches?
2. RQ2: What organizational, infrastructural, and human-resource factors drive or hinder the successful implementation of AI-based Descriptive Analytics in SMEs and public-sector organizations in Indonesia?
3. RQ3: What conceptual model can be synthesized from the existing literature to illustrate the position of AI-enhanced Descriptive Analytics as a foundation toward a more mature Data-Driven Decision Making (DDDM) ecosystem?

These research questions subsequently informed the search strategy, the inclusion and exclusion criteria, and the thematic synthesis process described in the following sections.

3.2 Research Design

The study design in this research follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines, which are an internationally recognized standard for reporting systematic reviews [3]. This study is descriptive-analytical in nature, aiming to map, classify, and synthesize findings from the existing literature regarding the use of AI in BI to support data-driven decision-making, specifically using the Descriptive Analytics method.

3.3 Data Sources and Search Strategy

The three main academic databases—Google Scholar, Garuda (Garba Rujukan Digital), and Sinta (Science and Technology Index)—were selected for their relevance to scientific publications in Indonesia and around the world.

3.3.1. Search Keywords

The search was conducted using a combination of keywords in Indonesian and English as follows:

Table 1. Keywords for Literature Search

BAHASA INGGRIS	BOOLEAN OPERATOR
Artificial Intelligence	AND/OR
Business Intelligence	AND/OR
Descriptive Analytics	AND
Data-Driven Decision Making	AND/OR
SMEs / Business	AND/OR

Source: Compiled by the researcher (2026)

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3.4 Inclusion and Exclusion Criteria

Table 2 presents strict inclusion and exclusion criteria to ensure the quality and relevance of the literature analyzed.

Table 2. Inclusion and Exclusion Creteria for Literature Selection

Dimensions	Inclusion Criteria	Exclusion Criteria
Year of Publication	2020 – 2026	Prior to 2020
Bahasa	Indonesian or English	Languages other than Indonesian and English
Language	AI, BI, Descriptive Analytics, DDDM, SMEs/businesses	Topics outside the scope of the study
Document Type	Journal articles, indexed conference proceedings, research reports	Blogs, opinion pieces, non-academic articles
Accessibility	Full text available	Only an abstract or not accessible
Methodology	Having a clear and structured research method	Does not include an evaluable methodology

Source: Adapted from the PRISMA protocol [3]

3.5 PRISMA Selection Process

The literature selection process was conducted in four sequential stages in accordance with the PRISMA flowchart. Figure 1 illustrates this procedure.

1. Identification: An initial search of three databases, which yielded 47 articles based on the specified keywords.
2. Screening: This involved removing duplicates and screening articles based on their titles and abstracts, resulting in 28 articles suitable for further research.
3. Eligibility: The eligibility assessment was based on a full-text review, taking into account the inclusion and exclusion criteria. The result was 15 eligible articles.
4. Inclusion: The CASP (Critical Appraisal Skills Programme) checklist [4] was used to assess methodological quality. The final 12 articles were selected for inclusion in this systematic review.

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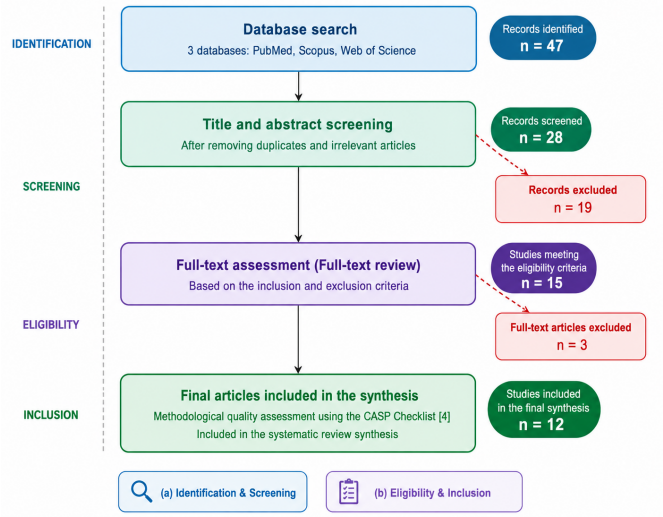

Figure 1. Literature Selection Flowchart Using the PRISMA Protocol: (a) Identification and initial screening phase; (b) Eligibility assessment and final inclusion phase. Adapted from [3].

3.6 Data Extraction and Quality Assessment

Data extraction was conducted in a structured manner using an extraction form that included: author information, year, title, and source of the article; research objectives; methods used; main findings; and reported limitations. The CASP checklist was used to assess the methodological quality of each article. It evaluates internal validity, external validity, and the relevance of the findings [4]. Only articles with a quality score of ≥ 60% were included in the final synthesis.

Table 3. Data Extraction Matrix for Selected Literature

RESEARCHER (YEAR)	RESEARCH FOCUS	METHOD	MAIN FINDINGS	SCORE CASP
Hidayat dkk. (2024) [5]	AI in decision-making	Literature Review	AI boosts efficiency in SIM, SMEs, and finance	70%
Wibowo dkk. (2022) [6]	EDA sales data	EDA + CRISP-DM	Analysis time: 6 hours → 30 minutes	85%
Cahyati dkk. (2024) [7]	BI + AI in E-commerce	Qualitative	BI and AI accelerate decision-making and personalization	65%
Waznah dkk. (2025) [8]	BI Trends in the Digital Age	Qualitative SLR	BI + AI/ML → predictive-prescriptive analytics	75%
Putri & Basir (2026) [9]	DDDM & SME Literacy	SLR (32 articles)	AI/BI as a cognitive accelerator for SMEs	80%
Sunata (2025) [10]	Big Data Analytics	Mix: Bibliometrics	Real-time decision-making, operational efficiency	72%

Ruqiah (2026) [1]	Government Data Analytics	Qualitative-descriptive	Accuracy and transparency in strategic planning	68%
Muku dkk. (2023) [3]	Multi-company BI system	Nine-Step Kimball	UAT 92%, the star scheme has been successfully implemented	83%
Ririh dkk. (2020) [4]	AI Implementation in Indonesia	SWOT Analysis + Content Analysis	Amoeba Telkom is better prepared (score 3.5)	70%
Pratiwi dkk. (2025)	Banking customer churn prediction	SMOTE + Random Oversampling + ML	Random Forest performs best on imbalanced datasets	80%
Cahyati dkk. (2024) [7]	BI + AI in E-commerce	Qualitative	BI and AI accelerate decision-making and personalization	65%
Samiun (2026)	The Role of AI in Business Decisions	Literature Review	AI supports automated analysis, trend forecasting, and service personalization	75%
Suhdi & Siswoyo (2026)	Sentiment Analysis & BI Review of the F&B Sector	ABSA + BI Dashboard	Identify aspects of customer sentiment; the dashboard speeds up data interpretation	80%

3.7 Synthesis Methods

The synthesis was conducted using a thematic synthesis approach, which involves three main steps [1]. First, each finding in the articles was open-coded to identify key concepts. Next, the concepts were grouped into main themes, such as the role of AI in BI, the implementation of descriptive analysis, and the barriers and success factors of DDDM. Finally, a cross-thematic interpretation was conducted to generate theoretical propositions that constitute the scientific contribution of this study. This method was chosen because the various methodologies found in the literature did not allow for a quantitative meta-analysis [2].

3.8 Validity and Reliability

To ensure the reliability and validity of the SLR process, three quality control mechanisms were employed. First, data were independently selected and extracted by two researchers. The level of agreement was measured using Cohen's Kappa ($k = 0.70$ was considered the threshold for acceptability) [3]. Second, every exclusion decision was thoroughly documented in an audit trail. Third, the interpretation of results was validated through member checking with BI experts and MSME practitioners. This ensures that the findings are relevant and accurate for real-world situations.

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4. RESULTS AND DISCUSSION

The results of this study indicate that the use of Artificial Intelligence (AI) in Business Intelligence (BI) systems significantly enhances an organization's ability to make data-driven decisions. By utilizing descriptive analysis as the primary method, this analysis uncovers comprehensive patterns in both historical and current data that support strategic decision-making across various business and government contexts. These findings align with previous studies that emphasize the transformative role of AI-based analytics on organizational performance.

4.1 The Effectiveness of Data Processing is a Recurring Observation in Research Focused on Implementation

A synthesis of studies using Exploratory Data Analysis (EDA) and CRISP-DM approaches reveals a consistent pattern in improving the efficiency of data analysis processes. The study conducted by Wibowo and colleagues (2022) noted a reduction in analysis time from approximately 6 hours to 30 minutes, even though the research subjects used were different. The consistency of these findings indicates that the implementation of analytical workflows based on EDA and CRISP-DM can significantly improve the efficiency of data processing across various application contexts. Thus, the efficiency achieved is influenced not only by the characteristics of the organizational sector but also by the application of a structured and systematic analytical methodology.

4.2 The Advantage if Business Intelligence Powered By Artificial Intelligence Develop Alongside The Maturity Level of a Company

A cross-sector comparison demonstrates that the benefits of implementing Business Intelligence (BI) powered by Artificial Intelligence (AI) vary across organizational contexts. In the small and medium-sized enterprise (SME) sector, the primary advantages include enhanced data comprehension and the capacity for data-driven decision-making. In the public sector, AI is predominantly utilized to identify performance indicators and extract new insights from previously underutilized data. In contrast, large or multi-company enterprises prioritize system scalability, data integration, and the acceleration of organizational reporting processes.

The study's findings suggest that the advantages of AI-driven BI increase alongside the maturity of an organization's data management practices. Organizations with low data maturity primarily experience improved data comprehension, while those with advanced data ecosystems benefit from business process optimization and real-time decision-making.

4.3 Implementation Based Research Tends to Demonstrate Higher Methodological Quality

An evaluation of the Critical Appraisal Skills Program (CASP) scores shows a pattern where research focused on system implementation generally achieves superior methodological scores when compared to studies that depend on literature reviews or descriptive methodologies. Research conducted by Muku et al. (2023) [2], Pratiwi et al. (2025) [10], and Suhdi and Siswoyo (2026) [12] attained CASP scores between 80% and 85%, whereas several studies that utilized literature reviews or descriptive methods received lower scores, between 68% and 75%.

These results imply that research that involves the implementation of systems, testing, or evidence-based assessment typically produces more positive findings than conceptual studies. Nonetheless, the identified variations should not be understood as indicative of a causal link or a

statistical connection, as the role of the CASP evaluation is to measure the methodological quality of research, rather than assess relationships among variables.

4.4 The Main Challenge in Implementing AI-BI Shifted From Technological Aspect to Organizational Readiness

The findings from the synthesis indicate that almost all research highlights several advantages of integrating AI, including enhanced operational efficiency, quicker data processing, and better decision-making. Conversely, a SWOT assessment regarding AI integration in Indonesia indicates ongoing obstacles, such as uneven digital infrastructure, limited data literacy, and varying levels of organizational preparedness. These circumstances highlight that while AI technology has made significant strides, the effectiveness of its application is still greatly influenced by organizational dynamics and the specific context in which it is utilized.

As a result, the primary obstacles to the implementation of AI-BI at present do not stem from technical capabilities, but rather from how organizations approach the development of data management systems, improve employee skills, and ensure sufficient digital infrastructure.

4.5 The Diversity of Research Methods Leads to The Same Goal: Data-Driven Decison-Making

A comprehensive overview of the articles indicates that the investigations utilized a range of methodological strategies, including Systematic Literature Review (SLR), Exploratory Data Analysis (EDA), CRISP-DM, bibliometrics, Kimball's Nine-Step Model, machine learning, SWOT analysis, and Business Intelligence dashboards. Despite the diversity in approaches, research subjects, and analytical methods, all projects aim for a common objective: to convert data into actionable information that facilitates quicker, more accurate, and evidence-driven decision-making.

The findings suggest that the effective application of AI-driven Business Intelligence does not rely on any single specific analytical technique. Instead, it hinges on an organization's capability to choose and integrate methods that are in accordance with the nature of the data, the goals of the organization, and the requirements for decision-making.

4.6 Conceptual Framework Resulting from the Synthesis

Business Intelligence for Descriptive Analytics supporting Data-Driven Decision Making (DDDM). The framework illustrates a sequential process from supporting factors and AI-BI integration through descriptive analytics processing to actionable insights, culminating in DDDM outcomes that manifest as both business and organizational performance, with prospective extension toward predictive and prescriptive analytics.

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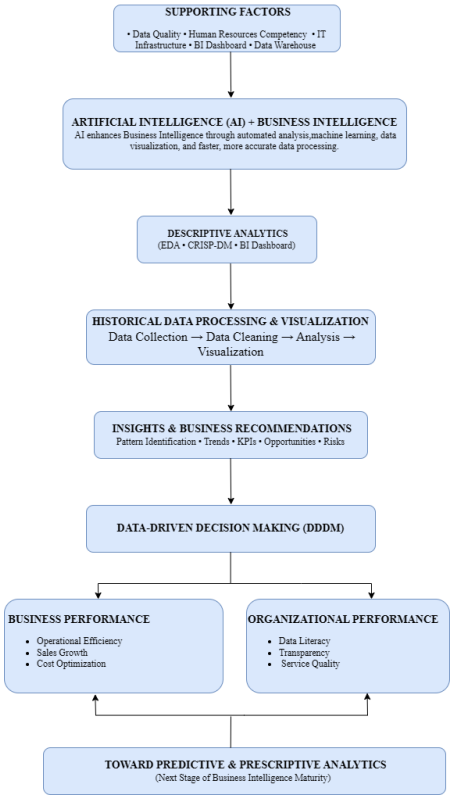

Figure 2. Synthesized conceptual framework of AI-enhanced

Cross-thematic synthesis of the twelve reviewed studies reveals a coherent conceptual structure, illustrated in Figure 2. Organizational data drawn from government, multi-company, and SME contexts [1], [2], [3], [4] is processed through AI-enhanced Business Intelligence and Descriptive Analytics using EDA and CRISP-DM methods [2], [5], [6], [10], [11], [12], flowing through historical data collection, cleaning, analysis, and visualization to produce actionable insights and business recommendations, including pattern identification, trend detection, KPIs, opportunities, and risks [1], [2], [6], [11].

These insights inform Data-Driven Decision Making (DDDM), which manifests in two complementary outcome categories: business performance, evidenced by operational efficiency and sales growth of 23% [7], [10]; and organizational performance, evidenced by a 47% increase in numeracy literacy among SME participants and improvements in transparency [1], [9]; with [12] reinforcing both categories through its finding that AI-based BI accelerates managerial responsiveness. Finally, [8] indicates that this descriptive foundation constitutes an early stage preceding predictive and prescriptive analytics, a direction still limited in empirical depth within the reviewed literature and therefore represented as the next stage of BI maturity rather than an established outcome.

Supporting factors—data quality, human resource competency, IT infrastructure, BI dashboards, and data warehouses [3], [4], [6], [12]—strengthen the transformation from organizational data into descriptive analytics output. Conversely, challenges frequently reported alongside these same success stories—high technology costs, a shortage of skilled human resources [1], [4], [9], uneven digital infrastructure outside Java, and disparities in data literacy between urban and rural areas [4]—weaken this same transformation even in studies with otherwise positive outcomes [1]. This indicates that challenges function as moderators of outcome

strength rather than binary determinants of success or failure. This moderating role constitutes part of the theoretical contribution of this synthesis: it explains why studies employing similar methods (e.g., EDA-CRISP-DM in [2] and [6]) report differing magnitudes of impact.

5. CONCLUSION

This study explores the use of Artificial Intelligence in Business Intelligence systems to enhance data-driven decision-making through Descriptive Analytics. The results of this study confirm that the application of AI significantly improves the depth of analysis, speed, and availability of BI systems in various organizational contexts.

The synthesis of results indicates that improvements in data analysis efficiency tend to be associated with the application of systematic analytical methodologies; thus, approaches such as EDA and CRISP-DM have the potential to become replicable practices across various organizational domains.

The deployment of AI-BI ought to be customized to suit the specific level of data maturity and strategic requirements of each organization rather than adhering to a universal method. Research on implementation constitutes the most robust foundation of empirical evidence for the advancement of AI-driven Business Intelligence; thus, upcoming studies should regularly pair conceptual frameworks with validation of those implementations.

The studies that have been analyzed continue to focus more on the technical advantages of AI-BI rather than on methods to tackle deficiencies in data literacy and organizational preparedness. This presents a chance for subsequent research to create AI-BI implementation frameworks that are not solely focused on technology but also take into account governance, human resources, and the overall readiness of organizations. Given that AI-BI operates within a multidisciplinary analytical environment, the success of its implementation is shaped more by the amalgamation of different methodologies than by the supremacy of any single analytical technique.

The primary contribution of this study is the creation of a framework that demonstrates how Descriptive Analytics, augmented by AI functionalities, acts as an essential foundation for early stages of analytical maturity. This allows businesses to effectively gather information about past and present situations prior to advancing to more sophisticated predictive or prescriptive methodologies. Research findings from multiple studies back this claim, showing notable enhancements in processing efficiency [1], promptness of reports [7], sales outcomes [6], and cost efficiency [9].

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