

Integrating Knowledge Engineering with Business Intelligence for Data-Driven Decision Making

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Abstract: Methods of making decisions based on data have become essential in enhancing performance and achieving competitive advantage among modern business organisations. While Business Intelligence (BI) can offer sophisticated ways to collect, process, and present data, it cannot leverage domain knowledge or engage in intelligent reasoning. The role of Knowledge Engineering (KE) is to add knowledge representation, business rules, and inference to the decision-making process. This paper proposes a framework that combines BI and KE to develop intelligent decision-support systems and enable explainable, intelligent business decisions. The proposed system is seen as a four-layer structure comprising a data management layer, a Business Intelligence (BI) analytics layer, a knowledge base and an inference engine. The data management layer is responsible for storing and retrieving necessary organisational data. The BI analytics layer processes this data to produce relevant analytical findings such as trends, indicators and performance statistics. The knowledge base consists of business rules, organisational policies, expert knowledge and specified decision criteria. Finally, the inference engine combines the analytical findings with relevant knowledge and business rules to provide appropriate suggestions and decision assistance. A retail business case involving customer segmentation, inventory management and business planning is used to demonstrate the applicability of the suggested framework and to show how integrated analytical and knowledge-based reasoning can support multiple organisational decision-making activities.

Keywords: Business Intelligence; Knowledge Engineering; Data-Driven Decision Making; Decision Support System; Knowledge Base; Inference Engine; Business Analytics; Intelligent Systems.

Cite as: H. H. K. Tin, L. S. E. M. Tohamy, M. S. A. M. Soliman, L. A. K. Abuelfadl, J. A. A. I. Ibrahim, and I. A. I. Y. Abdelmoaty, "Integrating Knowledge Engineering with Business Intelligence for Data-Driven Decision Making," *AVE Trends in Intelligent Computer Letters*, vol. 2, no. 2, pp. 100–110, 2026.

Journal Homepage: <https://avepubs.com/user/journals/details/ATICL>

Received on: 28/01/2025, **Revised on:** 27/03/2025, **Accepted on:** 08/06/2025, **Published on:** 05/06/2026

DOI: <https://doi.org/10.64091/ATICL.2026.000328>

1. Introduction

The rapid development of digital technology has greatly changed the way modern corporate organisations collect, process, analyse and use information in their everyday work. Organisations are increasingly reliant on digital technology to process transactions, communicate with customers, manage internal processes, monitor performance, and support strategic operations.

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In consequence, organisations are producing vast quantities of structured and unstructured data from transaction systems, customer contacts, social media platforms, corporate software applications and other digital channels [1]. Such data is becoming more widely available, providing organisations with significant potential to understand their operations and customers better. However, the enormous volume of data alone does not ensure superior decision-making. Organisations must be able to turn raw data into useful information and then use that knowledge to inform business decisions when appropriate [2]. Therefore, the ability to translate organisational data into actionable knowledge has become a key prerequisite for boosting organisational performance, increasing customer satisfaction and gaining a competitive advantage. Business Intelligence (BI) has emerged as a significant technical approach to enhance data-driven decision-making in organisations. Business Intelligence (BI) provides methods for gathering, integrating, processing, analysing and presenting organisational data in a way that is understandable and usable by decision-makers [6].

Using tools such as data integration, data warehousing, Online Analytical Processing (OLAP), dashboards, reporting systems, key performance indicators (KPIs), and data visualisation, managers can evaluate organisational performance from multiple perspectives [9]. BI systems enable decision-makers to access up-to-date and historical company information, recognise patterns, compare across different time periods or business divisions, track key indicators and identify potential management problems. These competencies enable organisations to transition from intuition-based decision-making to equipping decision-makers with quantitative information to inform planning and operational actions [3]. BI is critical when company conditions change frequently, and decision-makers need to react to large volumes of information [12]. For example, managers may need to consider sales performance, customer behaviour, inventory levels, marketing efforts, financial indicators and operational performance before making a decision [4]. BI systems can combine information from multiple organisational sources and deliver analytical insights through dashboards and reports. This may increase the availability of information and minimise the time to gather essential business indicators. BI has therefore become an important component of current decision-support frameworks in organisations. Although BI has great potential for data analysis and visualisation, traditional BI systems also have fundamental limitations. Traditional BI methods are primarily geared toward descriptive and diagnostic analytics [1].

They can tell us what has occurred, recognise patterns in past data, and assist managers in exploring possible reasons for observed changes. However, analytical results do not always justify the decision a decision maker should take in response to a given business scenario [5]. A dashboard may show that sales are down, inventory is up or that customer activity has changed. Still, these numerical observations do not necessarily contain the organisational knowledge needed to determine the most appropriate response. Again, the same analytical finding may be interpreted differently by different organisations, depending on their policies, objectives, operational procedures and specialist knowledge. Another problem is that traditional BI systems often lack a systematic way to incorporate domain expertise and explicit organisational reasoning into analytical decision-making. Business decisions are not only determined by numerical information, but also by organisational regulations, business rules, expert expertise, operational constraints and predefined decision criteria. This information may be embodied in organisational papers, standard operating procedures, managerial standards, or the experience of domain experts [6]. If this information is not incorporated into BI analytics, decision-makers may have to manually evaluate the analytical data and integrate it with their own knowledge for decision-making [3]. This can create differences in decision-making and may lead to less consistency between managers or departments. Knowledge Engineering (KE) is a field of Artificial Intelligence that provides a strategy to overcome this constraint by enabling the capture, representation, organisation and use of knowledge within intelligent systems.

Knowledge Engineering may make organisational expertise more explicit through knowledge bases, ontologies, business rules, and inference processes [7]. A knowledge base can contain information on organisational policies, domain concepts, expert knowledge, operational constraints, and predefined decision criteria. A reasoning engine can then use this knowledge to draw conclusions or make recommendations by applying logical reasoning to the information it has available. The inclusion of Knowledge Engineering in organisational decision support enables quantitative BI analysis to be enhanced with contextual and knowledge-based reasoning [1]. While BI can identify essential patterns and conditions in organisational data, KE can interpret these situations within the framework of organisational knowledge. For example, a BI system can detect that inventory levels have risen while product sales have fallen [8]. The results of such analysis give quantifiable evidence of a possible business problem. This knowledge-based system may then determine whether these conditions fulfil pre-set business standards and decide whether an inventory check, demand analysis, price evaluation or any other managerial action should be considered. This will allow the decision-support process to move from merely presenting analytical facts to delivering suggestions grounded in organisational knowledge [9]. The combination of Business Intelligence and Knowledge Engineering thus offers great prospects for the development of intelligent, explainable decision-support systems. An integrated system may employ BI to collect and analyse business data, and a knowledge base and inference engine to interpret the analytical results [10].

This combination can provide decision-makers with quantitative evidence and knowledge-driven suggestions. The analytical results are applied, taking into account the organisational policies, business rules, and the expert knowledge provided, in a way that ensures the derived decision-support process enhances the completeness and consistency of organisational decisions.

Another key advantage of BI and KE integration is explainability [9]. In many decision-support contexts, not only decision-makers but also the rationale behind the advice need to be understood. A proposal based on a mixture of analytic evidence and explicit business rules can be traced back to the conditions and knowledge that prompted the reasoning [11]. For example, if a recommendation is made because sales have fallen below an expected level while inventory has exceeded a predetermined threshold, the system can explain that the satisfaction of a particular business rule generated the recommendation. Intelligent proposals are easier for managers to grasp and evaluate when explanations are provided. This is particularly so where organisations need to be transparent, accountable and consistent in their decision-making. The integrated BI and KE method is useful across a wide range of organisational operations. Analytical data in customer relationship management can be linked with customer knowledge and business rules to facilitate customer segmentation, retention tactics and marketing decisions [12].

BI can be used in inventory management to track stock levels, sales patterns and demand indicators, and knowledge-based rules can be used to decide when inventory needs to be reviewed or acted upon. Analytical patterns used in fraud detection can be compared against predetermined criteria and organisational knowledge to identify suspicious actions [1]. In supply chain management, information on demand, inventory, suppliers and logistics can be linked to operational policies to support planning and intervention. In the same vein, strategic business management can utilise integrated analytical and knowledge-based information to support planning and resource allocation [13]. Customer segmentation is one area where the combination of BI and KE can give useful decision support [7]. BI analytics can detect patterns in client transactions, buying frequency, product preferences, and other available business metrics. These analytical results can be used with company information to classify clients according to pre-defined business criteria. Not only can an integrated system provide statistical client groupings, but it may also correlate segments with applicable business regulations and possible managerial actions [8]. For example, some client situations may lead to recommendations about retention, targeted marketing, or service enhancement. BI's analytical outputs can be contextualised within the organisational environment through the knowledge-based layer. Another key application area is inventory management. Firms need enough stock to meet client demand, but not too much [14].

BI can give you data on past sales, current stock levels, demand trends and product performance. But deciding on the action to take based on these indicators may require additional organisational knowledge. Business rules can be created for inventory reviews, replenishment, redistribution or reduction [2]. By integrating these rules into the analytical data generated by BI, the decision-support system can propose decisions grounded in quantitative evidence and organisational requirements [6]. Also, the combination of analytical and knowledge-based methodologies can be used in business planning and marketing decisions. BI can provide managers with information on sales trends, customer behaviour, market performance, and other organisational metrics [4]. The knowledge base may include strategic objectives, organisational policies, business constraints and decision criteria set by experts. The inference engine can then integrate these to make more aligned recommendations with the organisation's aims. This can help decision-makers bridge the gap between analytical findings and managerial action [5]. Despite the potential benefits of merging BI and information engineering, establishing such a system requires careful consideration of how organisational information is expressed and maintained. Expert knowledge needs to be elicited and converted into explicit rules or other appropriate knowledge representations [15]. The business rules must also be amended when organisational policies, operational processes or business situations change. Knowledge bases must be maintained appropriately to ensure recommendations align with the company's current needs.

This combination also needs to ensure that the analytical information is valid because knowledge-based reasoning depends on the quality and relevance of the information fed into the inference process. Previous research has addressed Business Intelligence and Knowledge Engineering as important technologies to support organisational activities. However, integrating analytical capabilities and knowledge-based reasoning remains an important area for developing more intelligent decision-support approaches. BI can provide organisations with rich quantitative information, whereas Knowledge Engineering can offer the methods needed to represent organisational expertise and apply reasoning. The synthesis of these talents can overcome the limitations that arise when analysis and reasoning are independent of one another. An integrated approach can thus link organisational data, analytical insights, domain knowledge, business rules and managerial recommendations more closely [16]. This paper addresses this need by proposing an integrated architecture of Business Intelligence and Knowledge Engineering to enable data-driven, knowledge-supported organisational decision-making [2]. The suggested architecture comprises four primary layers: the data management layer, the Business Intelligence analytics layer, the knowledge base, and the inference engine. The data management layer manages the storage and retrieval of organisational data. The BI analytics layer then processes this information to produce useful analytical conclusions such as trends, indicators, comparisons and performance statistics.

The knowledge base includes organisational policies, expert knowledge, business rules and pre-defined decision criteria. The inference engine then combines analytical results with applicable knowledge and business rules to generate appropriate recommendations and decision support [17]. The proposed integrated method is intended to deliver more than analytical information to decision makers. The framework aims to assist in producing judgments that are more intelligible, consistent, context-aware, and actionable by integrating quantitative evidence with explicit organisational knowledge and reasoning

methods [3]. The proposed approach is illustrated through a realistic case study of a retail company, covering customer segmentation, inventory management and business planning. The application fields involve integrating BI analytics with knowledge-based reasoning to translate organisational data into meaningful analytical discoveries, then transforming these findings into knowledge-based suggestions. The overall contribution of the proposed integration of Business Intelligence and Knowledge Engineering is to provide a basis for the development of intelligent decision support systems that integrate data analysis, organisational knowledge, reasoning and explainable recommendations within a unified decision-making process [1].

2. Literature Review

2.1. Business Intelligence

Business Intelligence (BI) is the term for a collection of technologies, applications and practices for gathering, integrating, analysing and presenting business information. As stated by Chen et al. [1], BI and analytics have evolved beyond conventional reporting and data warehousing to sophisticated analytical techniques that are capable of handling large-scale data and providing valuable business insights. BI enables organisations to convert raw operational data into meaningful information through technologies such as data warehousing, Online Analytical Processing (OLAP), dashboards, reporting and data visualisation. These capabilities enable managers to analyse past and current company data, identify patterns, compare organisational performance, and track key performance indicators.

BI is defined by Negash [2] as the process of gathering, integrating, analysing and presenting business information to support managerial decision-making. Therefore, BI can enable organisations to improve operational efficiency and strategic planning by delivering timely, relevant information to decision-makers. BI has progressively taken on predictive and real-time analytical capabilities as advanced analytics has risen. Sharda et al. [3] further explain the development of BI toward analytics, data science and Artificial Intelligence (AI) and show how organisations can employ increasingly advanced analytical approaches to gain insights from complex datasets. These advances have changed BI's role from simply reporting on past performance to assisting with prediction, planning, and more data-driven organisational decisions.

2.2. Knowledge Engineering

Knowledge Engineering (KE) is an important subfield of Artificial Intelligence that concerns the acquisition, representation, organisation and use of knowledge to solve problems in a particular domain. Russell and Norvig [4] define knowledge-based techniques as systems that use representational knowledge and reasoning procedures to obtain conclusions and facilitate intelligent problem-solving. A typical knowledge-based system consists of a knowledge base, rules, an inference process and tools for presenting or explaining the outcomes of reasoning.

Knowledge representation is especially significant, as organisational knowledge can comprise expert knowledge, policies, procedures, business rules, and domain-specific concepts. This information may be expressed in formal structures that computer systems can process and reason about. Power [5] stresses the relevance of knowledge, models and decision-support resources in assisting managers in solving organisational problems. KE can complement quantitative information with contextual knowledge and logical reasoning to support intelligent decision-making. This allows a system to go beyond representing information to evaluating conditions and offering appropriate actions based on specified organisational knowledge.

2.3. Business Intelligence and Decision Support Systems

A Decision Support System (DSS) is a computer-based information system that supports corporate or organisational decision-making activities. Power [5] defines DSS as computer-based systems that help decision makers by integrating data, analytical models and decision-oriented skills. Thus, BI can be seen as an important analytical component in wider decision-support settings, providing tools to translate organisational data into usable analytical information. BI and DSS technologies can support managerial decision-making by integrating data, analytical techniques, reporting, visualisation and decision-oriented applications, as stated by Sharda et al. [6]. Traditional BI systems do particularly well at providing descriptive information about organisational performance and at identifying trends and patterns in business data.

But complex judgments in organisations may require more than quantitative proof. Managers may also need organisational policies, expert knowledge, business rules, restrictions and contextual information to decide on an appropriate reaction. Davenport and Harris [7] highlight the strategic value of analytics for organisations and explain how the systematic application of data and analytics capabilities can yield competitive advantage. But analytical results still need appropriate managerial interpretation and organisational context. Thus, combining BI skills with knowledge-based reasoning can yield a more robust decision-support system in which analytical outputs are interpreted in light of explicit organisational knowledge.

2.4. Integration of Knowledge Engineering and Business Intelligence

The merger of Knowledge Engineering and Business Intelligence offers the potential to integrate quantitative analysis with company knowledge and reasoning. Chen et al. [1] highlight the growing significance of analytics in converting organisational data into business insights. In contrast, Russell and Norvig [4] describe the importance of knowledge representation and reasoning for intelligent systems. By combining these views, organisations can integrate analytical evidence with domain expertise to support business decisions. BI can identify patterns, trends, anomalies and performance indicators from vast amounts of organisational data in an integrated manner. The knowledge engineering component then interprets these analytical results using business rules, organisational regulations, expert knowledge and established decision criteria. BI, for instance, might detect falling sales and rising inventory levels, and the knowledge base might have a rule stating that this combination of circumstances necessitates a reassessment of inventory or price. The inference mechanism can evaluate the relevant conditions and make a recommendation based on analytical data and organisational knowledge. Ontologies and other knowledge representation systems can further support this combination. Ontologies are key mechanisms for representing the concepts and relations of a particular domain, according to Staab and Studer [8]. An ontology can be used to depict relationships between consumers, goods, departments, processes, policies and commercial activities in an organisational context. This organised knowledge can provide additional context for the BI's analytical conclusions and support more coherent reasoning. Integration can also enhance the consistency of decision support. Consistent reasoning processes can evaluate similar business contexts if business rules and organisational regulations are explicitly stated in a knowledge base. This can limit the diversity produced by differing interpretations of organisational policies. Furthermore, an integrated system can potentially improve explainability, as recommendations can be related to the analytical evidence and rules that generated them. Thus, decision-makers are provided with a suggestion and its rationale. The BI journey to analytics, data science and AI has further raised the possibility of integration. Sharda et al. [3] address the potential uses of sophisticated analytics and AI to uncover complex patterns in organisational data. These analytics skills can be enhanced by knowledge technologies that provide organisational constraints, business rules and domain-specific reasoning. Such a combination can be employed in customer relationship management, inventory management, fraud detection, supply chain management, marketing and strategic planning.

2.5. Research Gap

The significance of Business Intelligence, Knowledge Engineering and Decision Support Systems has been well documented in the literature. However, the capabilities of these technologies are frequently addressed and deployed as independent components. BI primarily involves the collection, integration, analysis and visualisation of data within organisations. Knowledge Engineering, in contrast, deals with the representation of knowledge, rules and reasoning. BI's increasing analytical power is demonstrated in Chen et al. [1] and Sharda et al. [3]. Russell and Norvig [4] highlight the importance of knowledge representation and reasoning in intelligent systems. Power [5] and Sharda et al. [6] further confirm the usefulness of decision-support systems in helping managers with company decisions. The identified gap thus concerns the need for an integrated methodology that combines BI analytical results with organisational knowledge and reasoning mechanisms within a single decision-support process. A traditional BI system may know that a certain business condition exists but may not have the contextual knowledge to determine what organisational action should follow. In contrast, a knowledge-based system may be able to provide rules and suggestions, but may not have direct access to continuously updated quantitative business information. The combination of the two methods can overcome these restrictions by binding together data, analytics, knowledge, reasoning and recommendations. This research gap motivates the proposed study, which aims to integrate Business Intelligence with Knowledge Engineering to support data-driven, knowledge-based organisational decision-making. The proposed approach combines the analysis of organisational data, a knowledge base composed of business rules and expert knowledge, and an inference mechanism that interprets the study's outcomes. Such a unified framework can provide decision-makers with analytical information, as well as contextual recommendations and explanations. The strategy aims to enhance decision quality, consistency, interpretability, and actionability, and to form a basis for intelligent decision-support applications in contemporary business organisations.

3. Proposed Framework and Research Methodology

3.1. Proposed Framework

The present research integrates two approaches into a framework for BI and KE. The integration comprises five main components: Data Sources, Data Management, Business Intelligence Analysis, Knowledge Engineering Component and Decision Support Interface, as depicted in Figure 1. The first stage in this process is called Data Sources, which includes enterprise databases, transactional data, CRM systems, ERP systems, and data from other external business sources. This diverse data is gathered through the Extract, Transform, and Load (ETL) process and stored in a data warehouse. Step two is the Business Intelligence Analytics module, which uses data mining, data visualisation, reporting and predictive analytics to extract trends and patterns from this data.

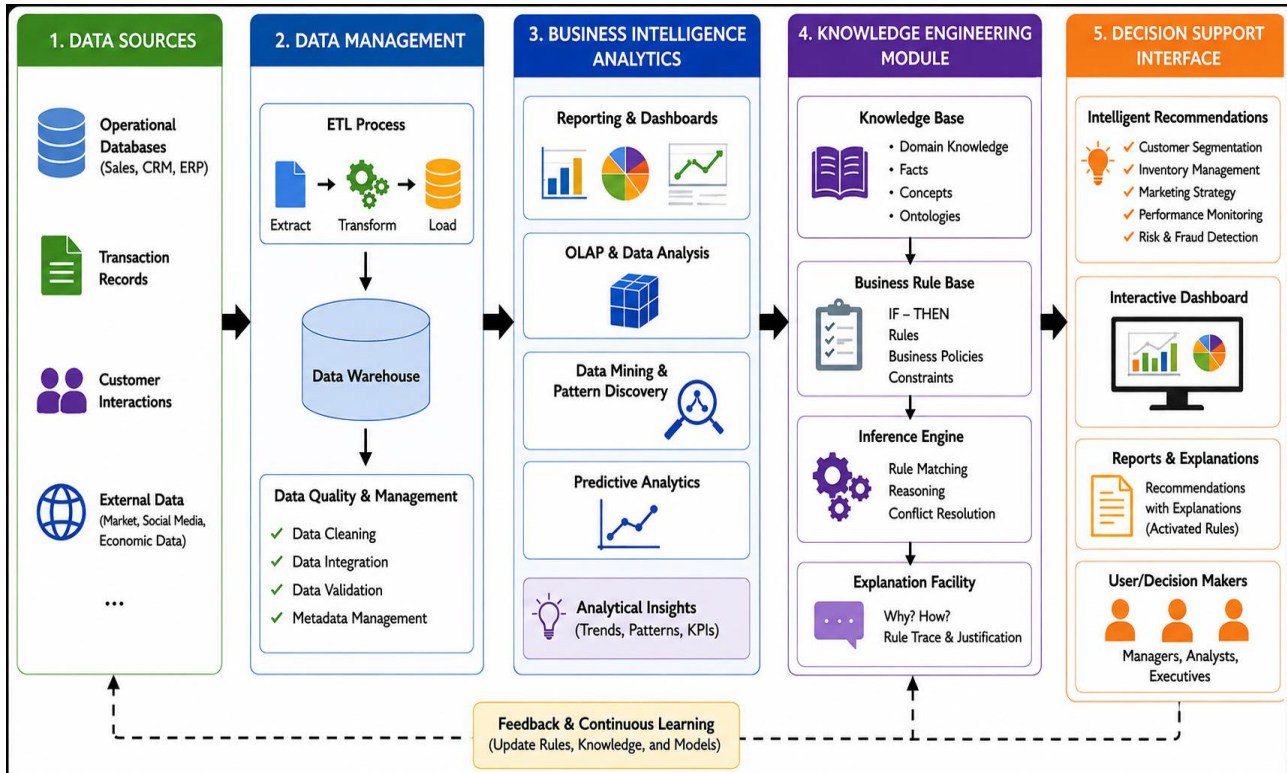


Figure 1: Proposed integrated framework

This data is displayed in dashboards and reports to enable managers to gain insight into how well their businesses are performing. Step three is the Knowledge Engineering module, which consists of a knowledge base, business rules, an ontology and an inference engine. The knowledge base comprises expert knowledge and organisational policies, while the inference engine performs logical reasoning to generate recommendations based on analysis results and predefined business rules. Lastly, the Decision Support Interface provides recommendations and insights from data analysis to decision makers through dashboards and reports.

3.2. Research Methodology

To propose an innovative solution, the study utilises the design science research methodology. It comprises four stages:

- **Problem Identification:** Examine the shortcomings of traditional Business Intelligence systems in facilitating intelligent reasoning and the requirement for incorporating Knowledge Engineering into their functioning.
- **Framework Design:** Propose an integrated conceptual framework that would combine Business Intelligence analytics with knowledge representation and reasoning techniques.
- **Prototype Demonstration:** Implement the framework in the context of a retail business, involving customer interactions, stock control and sales analysis. The implementation includes incorporating business rules into the knowledge base to provide intelligent recommendations.
- **Evaluation:** Evaluate the proposed framework in terms of decision quality, explainability, consistency and feasibility by applying scenario-based analysis and comparing it with traditional Business Intelligence approaches.

Thus, the presented methodology demonstrates how insights from Business Intelligence can be enhanced by knowledge-based reasoning techniques to support better decision-making. This framework can be easily adapted for use across industries such as retail, healthcare, finance, manufacturing and logistics.

3.3. Case Study and Prototype Implementation

3.3.1. Case Study

To illustrate the practicality of the suggested framework, a supermarket has been chosen as the case study. The supermarket generates vast amounts of business data from sales processes, purchases, inventory, and promotions. Despite this, managers make decisions based on their experience and intuition because the mentioned data is useful only if they know how to use it properly.

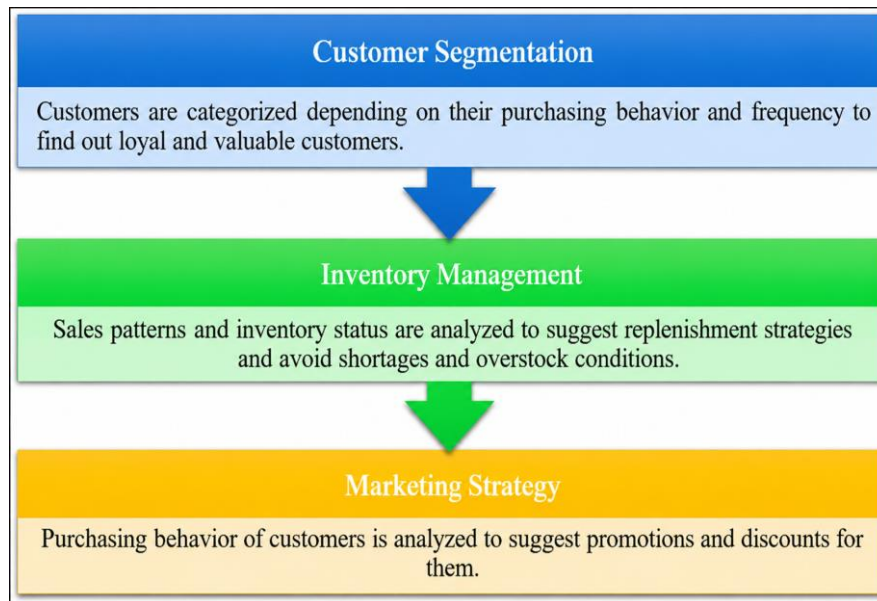


Figure 2: Three business scenarios

In contrast, the suggested framework combines approaches such as Business Intelligence (BI) and Knowledge Engineering (KE). Business Intelligence analyses historical sales and customer data to determine purchasing behaviour, product performance, and customer segments, while Knowledge Engineering uses business rules and expertise to interpret the analysis results. Three business scenarios were considered in this study, as presented in Figure 2. This case study highlights that combining analytics and knowledge-based reasoning improves business decision-making.

3.3.2. Prototype Implementation

A prototype of the proposed decision support system was developed to validate the conceptual framework. The prototype consists of five modules, as shown in Table 1.

Table 1: Five modules

Modules	Description
Data Management Module	Stores customer, sales, inventory, and product information in a relational database.
Business Intelligence Module	Performs data aggregation, reporting, dashboard visualisation, and basic predictive analysis.
Knowledge Base	Stores business policies, expert knowledge, and decision rules represented using IF–THEN production rules.
Inference Engine	Evaluates business rules against analytical results to generate intelligent recommendations.
User Interface	Provides managers with dashboards, reports, and explainable recommendations through an interactive interface.

The inference engine applies predefined business rules to analytical outputs, as shown in Figure 3. The BI module generates analytical reports from business data, which the inference engine analyses. Recommendations from the process are presented to the management team along with explanations using the active business rules. Explainable reasoning increases transparency and confidence in decision-making.

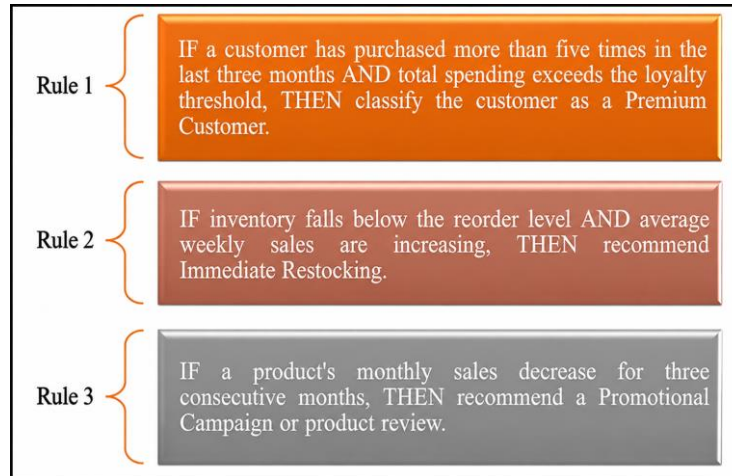


Figure 3: Predefined business rules

Finally, the prototype highlights the use of Knowledge Engineering and Business Intelligence to support decision-making through data analytics and expert knowledge. Even though this implementation is only a proof of concept, the prototype can be further improved by implementing machine learning algorithms, knowledge graphs, and real-time business data.

4. Results and Discussions

The construction of this prototype indicates that the combination of Knowledge Engineering (KE) and Business Intelligence (BI) can give a more complete form of data-driven decision support than the use of analytical capabilities alone. The BI part analyses sales transactions, customer behaviour and stock information to provide dashboards, indicators, trends and analytical insights. The results are subsequently sent to the KE component, where the inference engine evaluates the preset business rules. The ensuing recommendations bridge quantitative data and organisational expertise, providing managers with clearer, more practical interpretations of company realities. The prototype detects premium clients for customer segmentation based on purchase frequency and expenditure. If a customer's observed values meet predefined criteria, the inference engine classifies the customer as a premium consumer and outputs a targeted marketing recommendation. A simple prototype score is:

$$S_p = w_1F + w_2E \quad (1)$$

If S_p is the premium-customer score, F is the purchase frequency, E is the expenditure, and w_1 and w_2 are the respective weights. If the score exceeds a predefined level, the consumer can be selected for the premium section. In inventory management, the prototype identifies low-stock products with rising sales and suggests replenishment. Also highlighted are products with diminishing sales to seek promotional efforts before further degradation. Examples of how business rules can be used to analyse BI findings rather than present them as isolated dashboard indicators (Table 2).

Table 2: Prototype-Based decision support recommendations for different business areas

Decision Area	BI Analytical Finding	Knowledge/Rule Interpretation	Recommendation
Customer segmentation	High purchase frequency and expenditure	Premium criteria satisfied	Targeted marketing
Inventory management	Low stock + rising sales	Restocking rule activated	Replenish inventory
Inventory management	Declining sales	Low-performance rule activated	Consider promotion
Business planning	Performance trends	Planning criteria evaluated	Management review

Recommendation support can be theoretically formulated as:

$$R_s = (N_s / N_t) \times 100 \quad (2)$$

where R_s is the percentage of support for the proposal, N_s is the number of supporting analytical criteria (or rules), and N_t is the total number of relevant conditions under consideration. The equation is an example and not a result from a measured prototype.

4.1. Integrated Decision Flow

Figure 4 shows that the organisational data are initially processed using BI analytics. The knowledge base provides business rules and organisational policies.

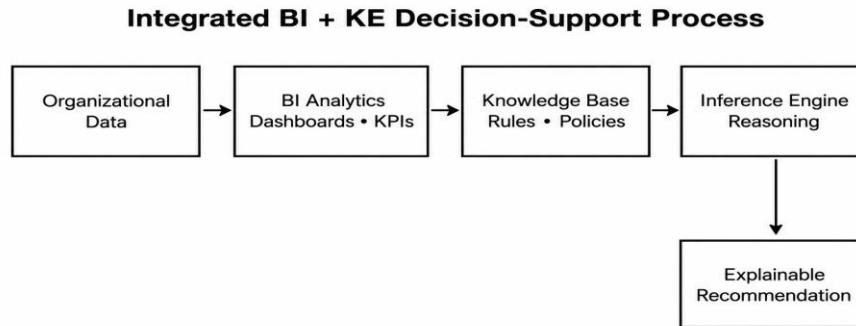


Figure 4: Conceptual flow of the proposed integrated BI and KE decision-support process

The inference engine combines analytical results with relevant knowledge to provide an explainable recommendation. This framework enables the transition from descriptive information to knowledge-based decision support.

4.2. Discussion

The findings show that BI and KE integration can enhance organisational decision support through linking data analysis to contextual reasoning. BI extracts meaningful information and patterns from corporate data effectively, while KE transforms the analytical results into actionable knowledge with rules and logical inference. One of the biggest benefits is explainability. Recommendations are based on explicit business principles so that users can understand the conditions and logic behind a recommendation rather than an unexplainable black-box output. This can increase managerial confidence and communication between business users and technological experts. The framework is also adjustable at the knowledge level. New business rules, organisational policies and expert knowledge can be introduced or amended without a major redesign of the four-layer architecture. A conceptual rule-priority measure can be formulated as:

$$P_r = W_r \times C_r \times S_r \quad (3)$$

where P_r is rule priority, W_r is rule importance, C_r is trust in support information, and S_r is significance of the business situation. This equation is a conceptual representation, not an experimentally determined value. However, the prototype has some shortcomings. Today's implementation uses a limited set of business rules and shows the framework with a single retail business case. Thus, the findings cannot be generalised to performance across different organisations or industries. Also, the current prototype does not include machine learning or streaming data. These constraints are essential because real organisational settings may involve rapidly changing data, larger knowledge bases, more complex relationships, and uncertain conditions (Table 3).

Table 3: Comparison of the current prototype and potential future enhancements

Aspect	Current prototype	Potential enhancement
Data	Retail transactions and indicators	Real-time/streaming data
Reasoning	Predefined business rules	Rules + machine learning
Knowledge	Small knowledge base	Knowledge graphs
Recommendations	Rule-based	Predictive + explainable
Scope	Single retail case	Multiple organizations

In future development, the system can be expanded by adding predictive machine learning algorithms, knowledge graphs and large language models. Machine learning may detect trends and generate forecasts, while the knowledge-based layer could incorporate organisational constraints and support explainable reasoning. Knowledge Graphs can describe the relations between customers, goods, policies, procedures and business entities. Large language models may enable natural-language interaction and knowledge extraction, but their outputs would need to be appropriately validated and governed. The overall prototype

demonstrates the potential value of combining Knowledge Engineering and Business Intelligence for data-driven organisational decision-making. BI provides quantitative evidence, while KE provides context, rules, reasoning and explanations. These features, working together, can help drive fuller, more consistent, comprehensible, and actionable suggestions. The customer segmentation and inventory management cases in retail highlight the potential of the integrated reasoning process to help various business decisions. Before general judgments about efficacy can be made, further empirical research is required, employing real organisational data, broader rule bases, real-time data, and quantitative decision-quality indicators.

5. Conclusion and Future Work

In this paper, an integrated framework combining Business Intelligence (BI) and Knowledge Engineering (KE) is proposed to support intelligent, data-driven decision-making. Though BI systems are highly efficient at gathering, processing, and visualising business information, the use of KE techniques further enhances their efficiency by leveraging domain knowledge, business rules, and logical inference. Thus, the proposed framework combines data analysis with knowledge bases and inference engines to produce intelligent, consistent recommendations for decision makers. The retail business case study demonstrates the usefulness of the framework for customer segmentation, managing inventories, and marketing strategies. The prototype demonstrates that a combination of analytical and knowledge-based reasoning results in better-quality decisions and greater transparency, which can be used to enhance business processes. Compared with existing BI systems, the proposed approach provides not only analytical information but also its logical justification, thereby enhancing confidence in the decision-making process. The study demonstrates that integrating Business Intelligence and Knowledge Engineering is a successful, scalable strategy for developing next-generation intelligent decision support systems. This strategy may be easily implemented in various business areas, including health care, finance, manufacturing, logistics and e-commerce. The following recommendations could be made for the future development of this research area. First, the suggested framework could be implemented and tested on a sample of real-world organisational data to assess its efficiency in business environments. Second, machine learning and deep learning techniques could be incorporated into the framework to enhance prediction abilities and knowledge generation. Third, knowledge graphs and semantic web technologies could be employed to enhance knowledge representation and reasoning across various business domains. Fourth, the framework could be enhanced by incorporating LLMs and XAI approaches.

Acknowledgement: The authors sincerely acknowledge the University of Information Technology and Zewail City of Science and Technology for their valuable support and contribution to this work.

Data Availability Statement: The data for this study are available upon request from the corresponding author.

Funding Statement: This manuscript and research paper were prepared without any financial support or funding.

Conflicts of Interest Statement: The authors have no conflicts of interest to declare. This work represents a new contribution by the authors, and all citations and references are appropriately included based on the information utilised.

Ethics and Consent Statement: This research adheres to ethical guidelines and obtains informed consent from all participants. Confidentiality measures were implemented to safeguard participant privacy.

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