

Information Technologies in Managerial Decision-Making Foundations and Application

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Management Information Systems

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CHAPTER III

BUSINESS INTELLIGENCE ARCHITECTURES IN MANAGEMENT INFORMATION SYSTEMS

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1. Introduction

In the era of digital transformation, organizations' competitive advantage no longer depends solely on the resources they possess but increasingly on their ability to make informed, data-driven decisions. Today, businesses operate in complex environments saturated with large and diverse datasets generated by multiple systems. Transforming these data into meaningful information and integrating them into strategic decision-support mechanisms have become essential for achieving sustainable success. Within this context, Business Intelligence (BI) and Management Information Systems (MIS) emerge as key components of the data-driven management paradigm.

Business intelligence constitutes a comprehensive framework that enables organizations to analyze their historical and real-time data in order to derive insights and forecasts about the future. These systems integrate the processes of data collection, transformation, storage, analysis, and visualization, thereby empowering managers to make faster, more accurate, and strategically informed decisions. Management information systems, in turn, provide the informational infrastructure that organizes the enterprise-wide flow of data, integrates operational processes, and supports decision-making activities. The integration of BI and MIS not only enhances consistency and reliability in data management

but also enables organizations to develop agile and forward-looking management models.

In recent years, the widespread adoption of big data analytics, cloud computing, the Internet of Things (IoT), and artificial intelligence (AI) has profoundly transformed BI architectures. Traditional reporting systems have evolved into real-time data processing environments that incorporate both predictive and prescriptive analytics. As a result, organizations can now address not only the question "What happened?" but also "What will happen?" and "Which strategy is most appropriate?". This evolution has repositioned management information systems from merely operational support tools into strategic infrastructures that create organizational value.

This chapter explores the integrated relationship between BI architectures and management information systems. It first discusses the conceptual foundations and historical evolution of BI, followed by an explanation of its core components-data sources, data warehouses, analytical layers, and performance management. Subsequently, data management and Extract-Transform-Load (ETL) processes are examined in the context of big data. The later sections analyze the functional application areas of MIS-Customer Relationship Management (CRM), Supply Chain Management (SCM), Enterprise Resource Planning (ERP), and Decision Support Systems (DSS)-together with the BI architectures utilized in these domains. Finally, the chapter discusses how the integration of BI and MIS contributes to strategic decision-making processes, competitive advantage, and digital transformation capacity.

2. Business Intelligence

Business Intelligence (BI) refers to the comprehensive integration of big data, analytical techniques, and DSS into organizational decision-making processes. Its purpose is not only to solve specific problems but also to develop enterprise-wide data solutions that can be utilized by decision-makers across all departments. Therefore, a BI approach that lacks analytical capabilities fails to deliver the expected benefits.

There is a strong relationship between BI and DSS. While DSS typically focus on specific users or problems, BI seeks to foster an organization-wide analytical culture. In particular, data-driven DSS represent one of the fundamental components of BI applications.

To understand the evolution of BI, it is essential to examine its historical development. The term was first introduced in 1958 by IBM researcher Hans

Peter Luhn, and during the 1960s-1980s, DSS gained prominence. In the 1990s, with the emergence of data warehouses, Online Analytical Processing (OLAP) systems, and first-generation BI software, BI applications became increasingly widespread. Since the 2000s, BI solutions offered by major software providers such as SAP, Oracle, and Microsoft have been widely adopted at the enterprise level.

From a technological perspective, BI has evolved from traditional reporting and retrospective analysis to real-time data processing, big data technologies, and cloud-based solutions. While traditional BI focused primarily on historical reporting, modern BI-supported by advanced analytics and machine learning techniques-can now generate future-oriented insights and prescriptive recommendations. Today, with the support of artificial intelligence, BI systems can answer not only the question "What happened?" but also "What will happen?" and "Which decision is most appropriate?".

The core components of BI include:

- Data sources and integration, which enable the collection and consolidation of data from multiple origins;
- Data warehouses, which structure data in a meaningful and accessible way;
- Data management and data quality, ensuring accuracy and reliability;
- Performance management systems, which track organizational objectives;
- Advanced analytical methods, providing predictive and prescriptive insights;
- Reporting and visualization tools, which communicate information clearly;
- Dashboards, delivering real-time insights to decision-makers;
- Strategy and governance frameworks, aligning analytical processes with organizational culture; and
- Security and compliance mechanisms, safeguarding data integrity and confidentiality.

In today's business environment, BI is no longer a tool reserved solely for executives; it has evolved into a democratized system accessible to all employees through self-service BI applications. Trends such as mobile access, cloud-based infrastructures, real-time analytics, and data storytelling have made

BI more flexible, accessible, and user-friendly. In this regard, BI is not merely a technical system but a strategic management tool that enhances organizational competitiveness, institutionalizes a data-driven culture, and improves the quality of strategic decision-making.

2.1. Core Components of Business Intelligence

BI is a multi-layered system that enables organizations to transform raw data into strategic knowledge. The fundamental components of this structure encompass a set of interrelated processes ranging from data collection and integration to analysis, visualization, and strategic governance.

1. Data Sources and Integration: This component ensures the collection and consolidation of data from diverse internal and external systems into a coherent structure. By maintaining data integrity, it establishes a solid foundation for subsequent analytical processes.
2. Data Warehouses: Data warehouses allow for the organization and storage of data in formats suited to content analysis, pattern recognition, and various analytical needs. They provide decision-makers with fast and systematic access to both historical and real-time information.
3. Data Quality and Data Management: This component ensures the accuracy, integrity, reliability, and timeliness of data. It represents a critical determinant of the overall credibility and validity of BI outputs.
4. Reporting and Visualization: This process facilitates the clear and effective presentation of complex data through standardized or dynamic reports. Well-designed visualizations enhance users' comprehension of information and foster more active participation in decision-making processes.
5. Advanced Analytics: Utilizing predictive and prescriptive analytical techniques, this layer generates forecasts and alternative decision scenarios. It functions as an advanced analytical domain that supports strategic planning, foresight, and evidence-based decision-making.
6. Performance Management Systems: These systems enable the continuous monitoring and assessment of organizational objectives, business processes, and key performance indicators (KPIs). As a result, corporate strategies can be dynamically refined based on measurable, data-driven insights.
7. Dashboards and User Interfaces: Dashboards and interactive interfaces provide decision-makers with immediate, intuitive, and visually engaging

access to information. These tools significantly enhance the responsiveness and efficiency of real-time decision-support mechanisms.

8. Corporate Strategy and Governance: This component ensures that BI processes are embedded within the organizational culture, aligned with strategic objectives, and seamlessly integrated into managerial decision-making structures.

9. Security and Compliance: This dimension guarantees that data confidentiality, integrity, and compliance with legal and regulatory frameworks are maintained throughout all BI processes. It is particularly vital for ensuring data protection and cybersecurity in the context of personal and sensitive information.

When these components operate cohesively, organizations are able not only to evaluate their past performance but also to generate future-oriented insights that strengthen strategic decision-making. Thus, BI should be regarded not merely as a technical system but as a holistic managerial approach that shapes analytical capability, enhances decision quality, and reinforces organizational culture. In today's competitive environment, a firm's capacity to achieve sustainable advantage is directly associated with the maturity level of these components.

2.2. Data Management

In today's digital era, the role of data has become more strategic than ever before. Organizations now generate vast amounts of data through every transaction, customer interaction, and digital touchpoint. This diversity of data - spanning from sales records and operational processes to social media content and customer experiences - appears in both structured formats (e.g., database records) and unstructured formats (e.g., images, videos, and comments).

In recent years, the exponential growth of data in terms of volume, velocity, and variety has placed the concept of big data at the center of attention. Big data does not merely refer to the vast quantity of information; it also describes data that are produced at extremely high speeds, from numerous heterogeneous sources, and often in irregular formats. When not properly managed, these characteristics can lead to complexity and inefficiency in organizational decision-making processes.

This is where the concept of data management becomes essential. Data management is not limited to the collection of data; it also encompasses the cleaning, validation, secure storage, and preparation of data for analysis.

Without an effective data management process, big data remains merely a mass of information that cannot be transformed into meaningful insights.

When properly managed, data become a strategic asset for organizations. Data management provides the foundational infrastructure for BI systems, analytical applications, and reporting processes. It enables organizations to make evidence-based rather than intuition-driven decisions, support their strategic objectives, and achieve sustainable competitive advantage.

Indeed, the amount of data flowing through sensors, mobile devices, social media platforms, and enterprise systems is increasing at an extraordinary pace. The total volume of data produced worldwide has approximately doubled every three years since the 1980s. In 2022, the global data production exceeded 100 zettabytes, and this growth is expected to continue in the coming years (Statista, 2023). To illustrate this scale, Figure 1 presents the annual global data production volumes between 2010 and 2027.

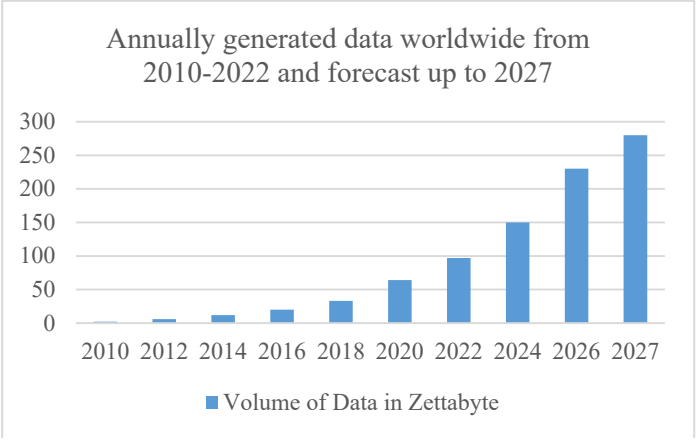


Figure 1. Global data production volume by year (2010-2027).

Data management is a strategic approach encompassing all processes related to the collection, storage, protection, analysis, and sharing of organizational data. In today's digital economy, effective data management is critical not only for operational efficiency but also for strategic decision-making and competitive advantage. The primary objective of data management is to ensure accuracy, integrity, security, and accessibility at every stage of the data lifecycle. Generally, the process includes six main stages: data collection, data preparation, data storage, data analysis, data distribution, and data integration.

Data Collection: This stage marks the starting point of the process and ensures the systematic acquisition of information required for organizational

decision-making. Data may originate from internal systems (e.g., CRM, SCM, ERP) or external sources (e.g., social media, open data, market research, web scraping). They can exist in structured (e.g., database records), semi-structured (e.g., XML, JSON), or unstructured (e.g., emails, videos, customer feedback) formats. This diversity necessitates a carefully designed data collection strategy.

Data Preparation: Collected raw data are typically unsuitable for direct analysis. Therefore, they must be cleaned, transformed, and standardized. During this phase, missing records are completed, erroneous entries corrected, outliers removed, and data from different sources integrated. Furthermore, data are converted into the formats required by analytical tools (e.g., digitization, normalization), thereby enhancing data quality and ensuring reliable analytical outcomes.

Data Storage: The secure storage of prepared data is vital for the sustainability of data management. Depending on organizational needs, companies may adopt on-premise servers, cloud infrastructures, or hybrid models. At this stage, data warehouses, data lakes, and backup systems serve as key components. Relational Database Management Systems (RDBMS) such as Microsoft SQL Server and PostgreSQL, as well as NoSQL databases such as MongoDB and Cassandra, provide solutions tailored to different data types and workloads.

Data Analysis: Data analysis enables organizations to extract meaningful insights from their data. This process employs statistical techniques, machine learning algorithms, data mining methods, and visualization tools. Platforms such as Power BI, Tableau, and QlikView play a significant role in decision-support processes, while technologies such as Python, R, Apache Spark MLlib, and TensorFlow facilitate the development of complex analytical models. The objective is to identify historical patterns and produce predictive insights for the future.

Data Distribution: This is the final stage of the process, ensuring that analyzed data are delivered to the right stakeholders at the right time. Reporting systems, dashboards, and interactive visualizations are used to communicate analytical results to decision-makers. This step reinforces a data-driven decision-making culture and enables managers to take timely and informed actions.

Data Integration: At the core of the entire process lies data integration. Data stored across different systems and formats are combined using the Extract-Transform-Load (ETL) process. In this stage, data are extracted from multiple sources, transformed into standardized formats, and loaded into

analytical systems. Effective data integration ensures a unified and consistent view of information across the organization, forming the foundation for strategic analytics.

2.3. The ETL - Extract, Transform, Load Process

In BI systems, directly retrieving data from operational databases often results in performance degradation, data inconsistencies, and delays in analytical processes. Consequently, modern BI architectures have adopted the approach of transferring data obtained from operational systems into a separate data warehouse. This process, known as ETL (Extract-Transform-Load), consists of three fundamental stages and forms the foundation for ensuring the continuity and accuracy of data warehouses (Khan et al., 2024).

Similarly, Acar (2024) emphasizes that direct access to operational databases may negatively affect system performance and compromise analytical accuracy due to erroneous or unvalidated data. According to the researcher, the ETL process functions as a critical bridge between raw data and the information delivered to end users. When executed in integration with ERP systems, it significantly enhances the efficiency of BI architectures. Acar further notes that Application Programming Interface (API)-based integration provides a more reliable and sustainable solution for transferring data from ERP systems, especially when handling large data volumes.

The Extraction stage marks the starting point of data management. At this stage, data are collected from various operational systems, sensors, social media platforms, and cloud-based applications. Depending on the type of data source, the extraction process may involve retrieving relational, semi-structured, or unstructured data. Metadata generated in this phase provides information about the data's origin, format, and timeliness, thereby supporting the accuracy of subsequent steps (Seenivasan, 2023).

The Transformation stage is where raw data are refined and made suitable for analysis. During this process, data are cleaned, normalized, and corrected for missing or inaccurate values, while records from multiple sources are consistently merged. Furthermore, unnecessary details are eliminated, summary tables are created, and data are converted in accordance with the organization's data model to optimize BI system performance. This stage enhances data quality and enables the establishment of reliable decision-support mechanisms (Khan et al., 2024; Seenivasan, 2023).

In the Loading stage, the transformed data are transferred into the data warehouse or analytical systems. This operation is typically carried out through either batch loading or real-time loading. The selection of an appropriate loading strategy directly affects system performance and data accessibility. Once the loading process is complete, the data become available for analysis and reporting through BI tools.

In conclusion, the ETL process constitutes the fundamental mechanism that transforms raw data into meaningful information within BI systems. Each stage - extraction, transformation, and loading - directly determines data consistency, analytical precision, and the overall quality of decision support. By optimizing ETL workflows, organizations can achieve not only operational efficiency but also enhanced strategic foresight and analytical capability.

2.4. Data Warehouse

A data warehouse is a centralized system where organizations collect, transform, and store large volumes of data obtained from operational systems for use in decision-support processes. These systems provide a foundational infrastructure for multidimensional modeling, data cleansing, data loading, and analytical processing. The key components of a data warehouse architecture include source data, ETL processes, the data warehouse repository, and access and analysis tools. The overall architecture integrates these components through stages of planning, design, construction, and operational management, forming a cohesive and holistic environment.

According to Timakum et al. (2021), research on data warehouses has predominantly focused on themes such as data mining techniques, algorithmic performance, and information systems integration. In this context, data warehouse architectures hold strategic importance by storing organizations' historical data consistently, thereby enabling performance monitoring and analytical evaluation.

Data warehouses are defined by four core characteristics: subject-oriented, integrated, time-variant, and non-volatile. These attributes distinguish data warehouses from other data management systems. An effective data warehouse integrates, cleanses, and validates data from diverse sources in a standardized manner. It then stores this data historically, making it readily available for analysis. Through this process, fragmented information within the organization is consolidated into a single source of truth, ensuring consistency, reliability, and transparency in decision-making processes.

Data warehouses are typically integrated with data mining, OLAP, and reporting systems, providing managers with valuable strategic insights. This integration allows organizations not only to assess past performance but also to generate forecasts and support forward-looking strategic planning. However, data warehouse design and implementation also involve a number of challenges. Issues related to data integration, data quality, system performance, security, and data governance are critical for effective data warehouse management.

Thus, establishing a successful data warehouse depends not only on technological infrastructure but also on process management, data governance policies, and the enterprise data culture that supports these processes.

2.5. OLAP, Data Mining, Reporting, and Visualization

In BI architectures, analytical layers are the essential components that transform structured data stored in data warehouses into meaningful and actionable information. These layers encompass Online Analytical Processing (OLAP), data mining, reporting, and data visualization processes. Each of these components supports knowledge creation at different stages of the decision-support mechanism, thereby enabling managers to develop strategic insights.

OLAP technology represents a powerful approach to multidimensional data analysis. It enables users to examine data from various dimensions and summarize information at multiple levels of detail. Through operations such as slice, dice, drill-down, and roll-up, decision-makers can explore data from different perspectives. OLAP cubes organize information by dimensions such as time, product, and region, allowing for rapid querying and multidimensional analysis. Thus, organizations can perform in-depth analyses of complex datasets related to performance, sales, customer behavior, and supply chain processes.

Data mining focuses on uncovering hidden patterns, relationships, and trends within large datasets stored in data warehouses. Techniques such as classification, clustering, regression, association rule mining, and anomaly detection constitute the core analytical methods of data mining. These methods offer organizations valuable insights in areas such as customer segmentation, risk analysis, market basket analysis, and fraud detection. Within the BI context, data mining extends and deepens the summarized data produced by OLAP systems, enabling more advanced and predictive analyses.

The reporting layer is the stage at which analytical results are systematically presented to decision-makers. It delivers information at different levels, ranging from operational performance indicators to strategic management reports. Modern reporting tools (e.g., Power BI, Tableau, Qlik) provide real-time data access through intuitive, user-friendly interfaces, enabling managers to interact dynamically with information.

The visualization layer is the most user-centered component of BI. Through charts, heat maps, interactive dashboards, and data storytelling techniques, complex data are presented in a simple, coherent, and visually engaging manner. Visual analytics reduces cognitive load and helps managers make data-driven decisions more rapidly and effectively.

When integrated with other analytical layers, this multidimensional analytical structure creates a strategic value creation chain. Data mining techniques operate on the summarized outputs of OLAP systems to reveal hidden patterns, relationships, and trends; these insights can then be used to measure corporate performance through Key Performance Indicators (KPIs). Indeed, Dahr et al. (2022) demonstrated this process by integrating OLAP cubes with data mining results and aligning them with KPI indicators in a sales decision-support system.

Therefore, the integrated and efficient design of these analytical layers enables organizations to address not only the question “What happened?”, but also “Why did it happen?”, “What will happen?”, and “Which strategy should be pursued?” - facilitating higher-level analytical reasoning and evidence-based strategic decision-making.

2.6. Key Performance Indicators (KPIs)

KPIs are quantitative measures that demonstrate the extent to which an organization has achieved its strategic objectives. For example, the study A Survey on Exploring KPIs compiled existing methods for identifying, defining, and monitoring KPIs, emphasizing that “the selection of KPIs is critical to success” (Badawy et al., 2016). Furthermore, another study proposed that the process of KPI identification could be automated through the use of data mining algorithms, enabling KPI determination from historical data without requiring expert intervention (Sultan et al., 2017).

Within this framework, KPIs are not merely outcome measures but also tools for monitoring performance trends, supporting strategic decision-making, and fostering a culture of continuous improvement (Maté et al., 2017).

3. Management Information Systems (MIS)

MIS constitute one of the fundamental information infrastructures that support decision-making processes within organizations. MIS functions as a centralized information repository that collects and integrates data from diverse sources, including internal systems, external databases, social media platforms, and the internet. By processing, analyzing, and transforming data into meaningful information, MIS directly contributes to managerial decision-making, planning, and control processes (Laudon & Laudon, 2004).

Although the evolution of MIS spans several decades, the structure and functionality of these systems have continuously adapted to meet changing organizational needs. While fundamental requirements-such as strategy formulation, implementation, and performance monitoring-have remained relatively stable, more dynamic needs, including environmental scanning and the identification of opportunities and threats, have evolved rapidly (Skyrius et al., 2013). This demonstrates that the nature of information systems encompasses both cyclical and predictable, as well as irregular and unpredictable, dimensions.

According to Altarawneh and Tarawneh (2023), modern information systems management seeks to strike a balance between these two dimensions. While MIS supports stability in strategic planning and organizational decision-making processes, BI solutions emphasize more flexible, dynamic, and predictive analytical approaches. BI systems enhance organizations' capacity for adaptation and innovation through functions such as environmental monitoring, competitive analysis, operational optimization, and the establishment of early warning mechanisms (Nithya & Kiruthika, 2021; Altarawneh & Tarawneh, 2023).

Within this context, MIS and BI applications have become complementary systems. MIS provides the foundation for data integrity and enterprise-wide reporting, whereas BI systems generate added value by producing predictive models, trend analyses, and decision-support scenarios based on these data. Consequently, organizations are not only able to monitor their current status but also to engage in strategic foresight and develop a sustainable competitive advantage (Altarawneh & Tarawneh, 2023).

In recent years, the integration of big data analytics into MIS infrastructures has significantly enhanced the effectiveness of BI systems. Hossain et al. (2024) highlight that this integration extends MIS capabilities beyond retrospective reporting to encompass advanced functions such as predictive analytics and

real-time decision support. Through this integration, organizations can extract strategic insights from complex datasets, respond proactively to environmental changes, and strengthen their competitive positioning.

Therefore, MIS has evolved beyond a system confined to the organization of operational data and has become a core component of big data, cloud computing, and AI-driven BI infrastructures. This transformation reinforces organizations' data-driven decision-making culture and enables a more holistic, agile, and forward-looking approach to strategic management (Hossain et al., 2024).

3.1. Functional Application Areas in Management Information Systems

MIS constitute an integrated framework that supports an organization's overall information flow, decision-making processes, and operational effectiveness. In today's business environment, organizations require not only basic information systems for managing complex data and processes but also specialized systems designed for specific functional areas. Within this scope, core systems developed under the MIS umbrella-Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), Supply Chain Management (SCM), and Decision Support Systems (DSS)-serve as fundamental information infrastructures that enhance organizational competitiveness.

Customer Relationship Management (CRM) Systems: CRM systems enable organizations to manage all interactions with existing and potential customers. Their primary objectives are to improve customer satisfaction, optimize sales processes, and foster customer loyalty. By analyzing customer data, CRM systems personalize marketing campaigns and enable the implementation of data-driven marketing strategies. The core contribution of CRM lies in facilitating customer-centric decision-making and promoting evidence-based marketing practices.

Supply Chain Management (SCM) Systems: SCM systems manage the planning, execution, and monitoring of supply chain processes from raw materials to finished products. Their goals include reducing operational costs, increasing delivery efficiency, and optimizing inventory levels. These systems allow real-time data sharing among suppliers, manufacturers, distributors, and retailers. The key contribution of SCM is process optimization and enhanced visibility across the global supply chain.

Enterprise Resource Planning (ERP) Systems: ERP systems integrate and manage all core business functions-such as finance, production, accounting,

human resources, and inventory management-within a single unified database. Through ERP, data redundancy is eliminated, processes are streamlined, and cross-departmental coordination is strengthened. The primary contribution of ERP lies in integrated information management and improved operational efficiency.

Decision Support Systems (DSS): DSS provide analytical assistance to managers in addressing semi-structured or unstructured problems. They incorporate big data analytics, statistical modeling, scenario analysis, and AI-based forecasting techniques. DSS are typically integrated with data warehouses and BI tools. Their principal contribution is enabling analytical decision-making, enhancing strategic foresight, and reducing risk.

Although each of these systems supports different organizational functions, maximum effectiveness is achieved when they operate in an integrated manner. Data generated from ERP systems can be utilized in CRM analyses; SCM processes can be synchronized with ERP operations; and all of these data streams can be analyzed through DSS to produce strategic reports for managerial decision-making. Thus, MIS evolves from being merely an information storage system into a strategic decision-support infrastructure that fosters organizational intelligence, agility, and competitive advantage.

3.2. Data Sources in Management Information Systems

MIS are founded on the processes of capturing, processing, and transforming data from both internal and external sources into meaningful information that supports organizational decision-making. Kraus et al. (2021) emphasize that information systems management involves a continuous cycle of data acquisition and analysis that leverages contextual information to influence decision-making processes. This cycle enables a data-driven governance framework across both operational and strategic dimensions of the enterprise.

Contextual data refers to metadata that provides insights into the environmental conditions under which data is generated, thereby enhancing the decision-making context. Such data improves the analytical precision of decision-support systems and allows MIS to become more situational and predictive in nature.

Big data analytics has emerged as a transformative force in the modern business landscape, enabling organizations to extract valuable insights from vast, diverse, and dynamically generated datasets (Chen et al., 2012). Through these technologies, enterprises have gained the ability to fundamentally reshape

their operations, make data-driven decisions, enhance operational efficiency, and sustain competitive advantage (Davenport & Harris, 2017).

At the center of this transformation, MIS integrates the processes of data collection, processing, storage, and analysis to support decision-making across all organizational levels (Laudon & Laudon, 2004). MIS provides managers with timely, accurate, and relevant information, forming the backbone of organizational decision-making mechanisms (O'Brien & Marakas, 2008).

The data sources used in MIS extend far beyond internal operational databases. The system also captures data from external sources such as customer interactions, social media platforms, sensor data, web logs, supply chain systems, and market research. These multidimensional datasets are processed through advanced big data analytics tools, transformed into actionable insights, and subsequently used to guide strategic managerial decisions.

The data processing stage involves organizing, sorting, classifying, and summarizing the collected data in alignment with business planning needs. This transformation converts raw data into strategic information that can effectively support managerial decision-making (Sun et al., 2018). Internal data sources include ERP, CRM, and accounting systems, whereas external sources may consist of market research reports, customer feedback, social media data, and publicly available databases.

As the diversity of MIS data sources continues to increase, data quality and data governance processes have become increasingly critical. Data obtained from multiple systems, sensors, or digital platforms often suffer from issues of accuracy, integrity, consistency, and timeliness. Consequently, modern MIS architectures emphasize not only the collection of data but also its management in accordance with established quality standards. Data quality directly affects the reliability of analytical outputs and thus determines the overall accuracy of decision-support systems (Khatri & Brown, 2010). Today, organizations adopt data governance frameworks-comprehensive structures that manage the entire data lifecycle-to ensure the accuracy and reliability of information derived from both internal and external sources (Al-Htaybat & von Alberti-Alhtaybat, 2017).

Altarawneh and Tarawneh (2023) argue that information systems management should extend beyond data collection and analysis to include timely information delivery and flexible data structures. An effective MIS must deliver real-time information on organizational activities, support diverse output formats, and maintain compatibility with evolving digital infrastructures.

Moreover, the system should be scalable to accommodate new data dimensions and dynamic business needs.

Today, MIS data sources are no longer confined to traditional enterprise systems but increasingly draw upon Internet of Things (IoT) devices, cloud-based storage environments, and AI-driven analytical platforms. These next-generation sources provide real-time data streams that make decision-making processes more dynamic. IoT sensors, in particular, enhance the predictive capacity of MIS by continuously capturing data on supply chains, production activities, customer behaviors, and operational performance. Meanwhile, AI-driven systems analyze datasets to deliver automated pattern recognition and predictive decision support. These technologies have transformed MIS from a system focused solely on monitoring past performance into a predictive and adaptive decision-support infrastructure.

In conclusion, the data sources within MIS represent a comprehensive ecosystem that encompasses both internal and external information flows. This ecosystem not only strengthens an organization's data-driven strategic management culture but also forms the foundation for decision-support systems and BI applications (Hossain et al., 2024).

4. Business Intelligence Architectures and Management Information Systems Integration

4.1. Business Intelligence Architecture

In BI systems, the data flow process involves transforming raw data gathered from diverse sources into meaningful information that supports decision-making. The process begins at the data sources layer, where data is collected from various internal systems (e.g., ERP, CRM, accounting software) and external platforms (e.g., social media, market research, sensor data). The collected data is then extracted, transformed into appropriate formats, and loaded into a data warehouse through the ETL (Extract-Transform-Load) process for analytical use.

The data warehouse serves as the organization's centralized memory, storing integrated corporate data in a unified structure. The data stored within this architecture is modeled through OLAP cubes, enabling multidimensional analysis and rapid querying capabilities.

This architecture forms the foundation of decision-support systems by enabling the transformation of data into information and information into

actionable insights. Figure 2 illustrates the process in which data is gathered from both internal and external sources, processed through the ETL pipeline, stored in the data warehouse, analyzed via OLAP cubes, and finally presented to end users through interactive dashboards. This architecture represents an integrated BI framework that converts raw data into knowledge and knowledge into strategic decision support.

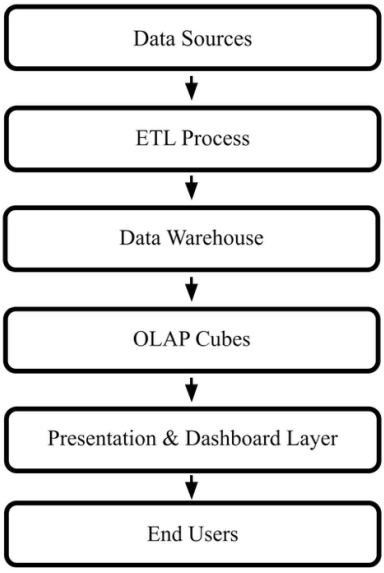


Figure 2. Layers of Business Intelligence Architecture

In conclusion, BI architectures are strategic structures that enhance organizations' data-driven decision-making capabilities by integrating the processes of data collection, transformation, storage, and conversion into meaningful insights. This general architecture can be implemented in specialized forms across different enterprise systems, such as CRM, SCM, ERP, and DSS. The following sections discuss BI architectures specific to these systems in greater detail.

4.2. Business Intelligence Architecture in Customer Relationship Management (CRM) Systems

CRM systems constitute one of the most advanced application domains of BI, enabling organizations to holistically manage, analyze, and transform customer data into strategic decisions. Figure 3 illustrates this architecture in detail, depicting the flow from data acquisition to analysis and action.

This architecture demonstrates the BI framework employed within CRM processes. The workflow begins with multiple data sources, including:

- Customer information (contacts, accounts, opportunities, activities) obtained from CRM systems,
- Campaign and customer journey data from marketing automation tools (emails, SMS, push notifications),
- Support tickets from IT Service Management and Customer Support (ITSM/CS) platforms, as well as call centers using Computer Telephony Integration (CTI),
- Event streams and conversion funnels from web and mobile analytics tools.

In addition, the architecture integrates:

- Customer feedback and sentiment analysis from social media and review platforms,
- Transactional data from billing and subscription systems (invoices, refunds, plan changes),
- Customer feedback metrics such as surveys, Net Promoter Score (NPS), Customer Satisfaction Score (CSAT), and Voice of Customer (VoC) results,
- Third-party data enrichment services (e.g., Clearbit for demographic and firmographic data),
- Digital advertising platforms (Google Ads, Meta Ads, TikTok Ads),
- Consent-management systems compliant with GDPR and the Turkish Personal Data Protection Law (KVKK).

All these data streams are ingested via batch and streaming methods into the data ingestion layer. During the ETL (Extract-Transform-Load) process, personal data masking (PII masking), normalization, and deduplication operations are performed. In the identity resolution phase, records are matched at the device, user, and account levels to create unified profiles.

The cleansed and standardized data are consolidated within Master Data Management (MDM) or Customer 360 layers into unified entities-customers, households, accounts, and touchpoints-and stored in data lakes or data warehouses using event-based or relational structures.

At the semantic model/OLAP layer, analyses such as customer segmentation, RFM (Recency-Frequency-Monetary), cohort analysis, and funnel metrics are generated. The advanced analytics and machine learning (ML) layer supports

models such as lead scoring, churn or propensity prediction, Customer Lifetime Value (LTV) estimation, Next Best Offer (NBO) and Next Best Action (NBA) recommendations, Multi-Touch Attribution (MTA), Marketing Mix Modeling (MMM), A/B testing, and uplift analysis.

The analytical outputs are delivered through dashboards and self-service BI tools, allowing end users to explore insights interactively. Using Reverse ETL processes, these analytical results are written back into operational systems to power campaign activation, ensuring that campaign and customer interaction outcomes are reintegrated into the CRM environment. This closed feedback loop continuously refines and updates predictive models.

On the user side, sales teams (Account Executives - AEs and Sales Development Representatives - SDRs) leverage BI outputs for pipeline management and sales forecasting, while marketing and growth teams utilize them for segmentation, personalization, and campaign management. Customer Experience (CX) and support departments, as well as product analytics, finance (e.g., revenue analysis, Customer Acquisition Cost - CAC), and compliance/legal teams, also benefit from these insights.

Finally, customer engagement occurs through multiple communication channels, including email, SMS, push notifications, ad-audience matching, on-site personalization, call-center actions, and automated task or ticket creation. This architecture enables the multidimensional management, analysis, and activation of customer data, providing a robust decision-support foundation for corporate customer-relationship strategies.

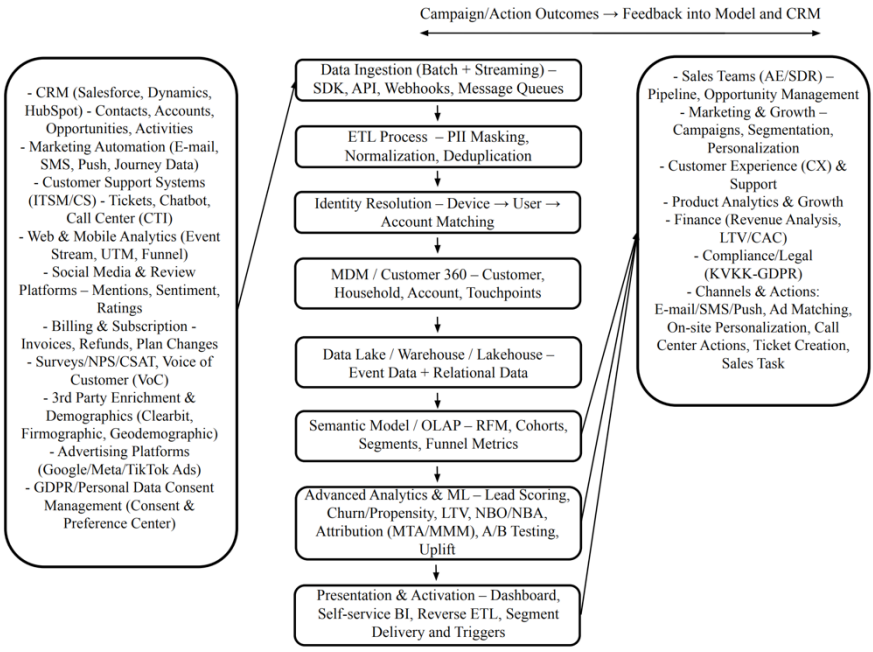


Figure 3. Layers of Business Intelligence Architecture for Customer Relationship Management Systems

This architecture supports data-driven decision-making across all customer-facing processes, enabling organizations to adopt a more holistic and predictive management approach in areas such as customer experience, sales performance, and strategic planning.

4.3. Business Intelligence Architecture in Supply Chain Management (SCM) Systems

SCM represents one of the most complex and data-intensive application domains of BI architectures. These systems integrate big data, analytics, and automation technologies to deliver operational visibility, decision support, and strategic foresight across all stages-from production to distribution.

Figure 4 illustrates the BI architecture designed for SCM processes. The workflow begins with data gathered from enterprise systems and operational infrastructures. Core data sources include orders, bills of materials (BOMs), and production plans obtained from ERP and Material Requirements Planning (MRP) systems. In addition, logistics infrastructures such as Warehouse Management Systems (WMS), Transportation Management Systems (TMS),

and Yard Management Systems (YMS) are integrated with process data collected from Industrial Internet of Things (IIoT) sensors on production lines and Manufacturing Execution Systems (MES).

Supplier portals feed the architecture through Electronic Data Interchange (EDI), AS2, and XML-based data exchanges, while Points of Sale (POS) and e-commerce platforms contribute sales data. Moreover, external data sources-including weather conditions, freight rates, commodity prices, and port or railway operations-serve as critical inputs for supply chain analytics.

These datasets are transferred to the data ingestion layer via both batch and streaming methods. At this stage, Change Data Capture (CDC) techniques, APIs, and message queue systems (e.g., Kafka, Message Bus) enable real-time data processing. The data then undergo the ETL (Extract-Transform-Load) process, which involves quality checks, cleaning, transformation, and integration.

Subsequently, within the Master Data Management (MDM) layer, supplier, product, location, Stock Keeping Unit (SKU), and taxonomy data are standardized. The data are then organized within Data Lake or Data Warehouse environments, where time-series and geospatial datasets are stored together to support comprehensive analysis.

At the next level, OLAP and semantic models enable multidimensional analyses of demand, supply, inventory, supplier performance, and geographical distribution. Within the Advanced Analytics layer, models are applied for demand forecasting, inventory optimization, safety stock (SS) and reorder point (ROP) calculations, network and route optimization, estimated time of arrival (ETA) prediction, anomaly detection, risk analysis, and early warning system development. Furthermore, Digital Twin applications facilitate simulation scenarios that enhance strategic flexibility in response to potential supply chain disruptions.

The analytical outputs are visualized through Supply Chain Control Tower dashboards, reports, and what-if scenario analyses. These visual tools enable users to monitor critical indicators such as demand-supply balance, production capacity, and logistics performance.

In the final stage, Sales and Operations Planning (S&OP) teams, procurement departments, warehouse and logistics operations, sales and channel management units, finance teams (for cost and profitability analysis), as well as suppliers and customers, all benefit from these analytical insights. Moreover, by leveraging Robotic Process Automation (RPA) and APIs, the system can automatically execute operational tasks such as purchase order creation, production plan updates, route changes, and inventory transfers.

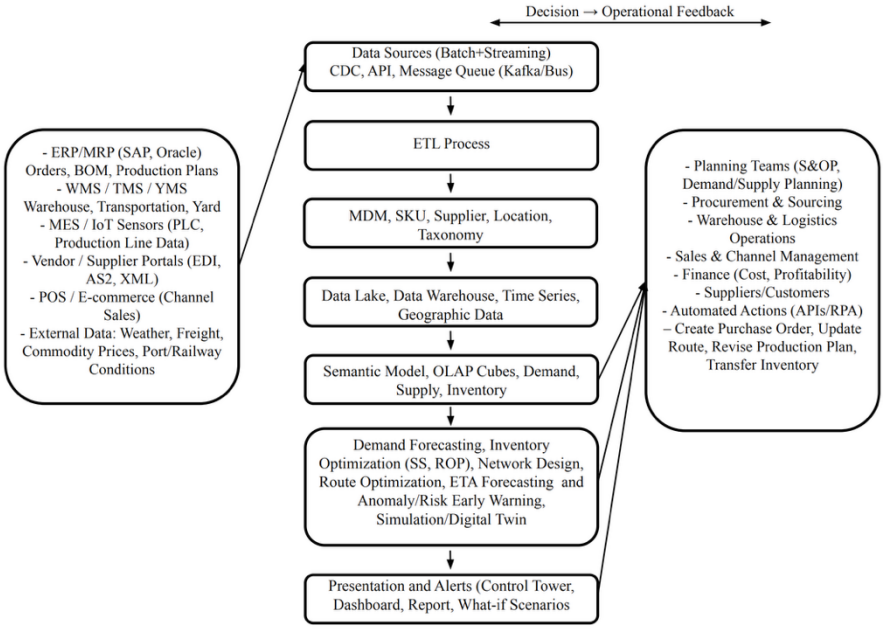


Figure 4. Layers of Business Intelligence Architecture for Supply Chain Management Systems

As a result, this architecture provides an integrated BI infrastructure that supports data-driven decision-making processes throughout the supply chain, enhancing both operational efficiency and strategic flexibility. Consequently, organizations can build predictive, adaptive, and resilient supply chain structures capable of rapidly responding to changing market conditions.

4.4. Business Intelligence Architecture in Enterprise Resource Planning (ERP) Systems

In today's business environment, the success of data-driven decision-making depends on the integrated analysis of information derived from enterprise systems. In this context, the integration of ERP systems with BI applications represents a crucial structure that enhances operational efficiency and supports strategic management decisions.

Figure 5 presents a comprehensive BI architecture designed for ERP systems. The process begins with data obtained from various ERP modules and external systems. The ERP system comprises several core modules, including:

- Finance and Accounting (General Ledger - GL, Accounts Receivable - AR, Accounts Payable - AP)
- Human Resources (HR) (payroll, performance, and training management)
- Procurement and Sourcing (purchase orders - PO, supplier and contract management)
- Production (bills of materials - BOM, material requirements planning - MRP, production line tracking)
- Inventory and Logistics (warehouse management, inventory, and distribution)
- Sales and Customer Order Management
- Project Management (budget, time, and resource utilization)
- Maintenance Management (Enterprise Asset Management - EAM, Computerized Maintenance Management Systems - CMMS)

Additionally, data from external systems such as banks, e-invoicing and tax authorities, as well as data collected from IoT and Radio Frequency Identification (RFID) sensors monitoring logistics and production processes, are incorporated into the system.

All these data streams are transmitted during the data ingestion phase through Application Programming Interfaces (APIs), Intermediate Documents (IDocs), Open Data Protocols (OData), and message queues. Subsequently, during the ETL (Extract-Transform-Load) process, data are cleansed, transformed, normalized across currencies and chart-of-accounts variations, and validated for integrity. At this stage, Master Data Management (MDM) ensures the standardization of customer, product, supplier, and location codes.

The processed data are consolidated within a Data Warehouse or Data Lakehouse architecture, integrating datasets across functional domains such as finance, human resources, procurement, production, inventory, and sales. Within the Semantic Model / OLAP layer, multidimensional analyses are performed, allowing organizations to examine financial statements, production metrics, procurement performance indicators (KPIs), and inventory turnover rates in detail.

At the Advanced Analytics and Machine Learning (ML) layer, predictive models are developed for demand and supply forecasting, production optimization, cost and profitability analysis, workforce planning, project performance evaluation, and predictive maintenance.

All insights are visualized in the Presentation and Reporting layer through dashboards, KPI cockpits, and self-service BI tools. These analytical outputs provide targeted insights for different organizational units:

- Executives (CEO, CFO, COO): financial reporting and strategic decision support
- HR managers: employee productivity and turnover analysis
- Supply chain teams: cost optimization and supplier performance
- Production and operations departments: capacity planning and efficiency monitoring
- Logistics units: inventory levels and route optimization
- Sales teams: order tracking and customer analysis
- Project managers: budget control and resource utilization
- Maintenance teams: fault prediction and scheduling support

Furthermore, external stakeholders such as banks, regulatory authorities, and auditing firms can also utilize these data for compliance and reporting purposes.

In conclusion, the ERP-centered BI architecture enables organizations to analyze all business processes from a holistic perspective, thereby improving operational efficiency while providing a strong, data-driven foundation for strategic decision-making.

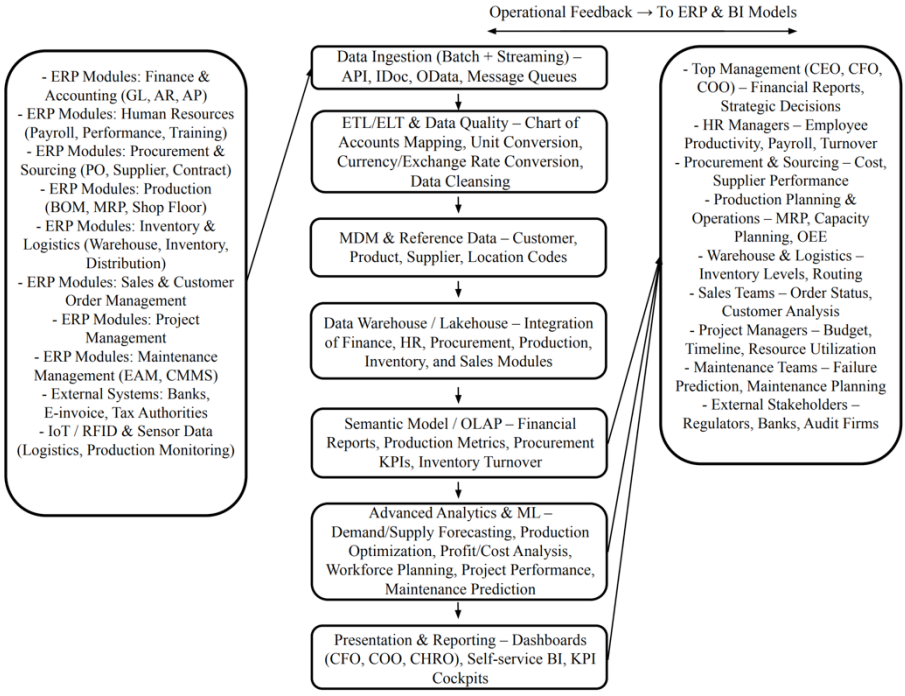


Figure 5. Layers of Business Intelligence Architecture for Enterprise Resource Planning Systems

As a result, this architecture not only enables organizations to monitor past performance but also allows them to make more accurate future plans, anticipate risks, and manage resources more efficiently.

4.5. Business Intelligence Architecture in Decision Support Systems (DSS)

In today's rapidly changing market environment, organizations must integrate not only historical data but also real-time and predictive insights into their decision-making processes to maintain a competitive advantage. At this point, DSS have become one of the core technological frameworks that interpret large and complex datasets to deliver analytical insights for managers.

Figure 6 illustrates a comprehensive BI architecture designed for DSS. The process aims to support decision-making by integrating both internal and external data sources through multi-layered analytical structures.

The process begins with data derived from Enterprise Systems, including ERP, CRM, SCM, HRM, and Production Systems. In addition, Operational

Databases, which record daily transactions and activities, constitute another key source of data.

Furthermore, external datasets are incorporated into the architecture. Market research, macroeconomic indicators, and competitive intelligence data are combined with outputs from Web and Social Media Analytics, such as trend analysis and sentiment analysis. Geographic Information Systems (GIS) provide location-based data, while simulation and scenario data support potential situation analyses. IoT and sensor-based data streams monitor operational processes in real time. Moreover, knowledge bases and reports containing scientific, technical, and statistical data enrich the organization's analytical environment.

All these data are integrated into the system during the Data Ingestion and Integration phase, which utilizes APIs, batch processing, real-time streaming, and external data connectors. The data then undergo the ETL (Extract-Transform-Load) process, where they are cleaned, transformed, and standardized. Within the Knowledge Management stage, master data sets and ontologies are created, giving the data a meaningful and semantically rich structure.

Subsequently, the data are consolidated within a Data Warehouse or Data Lakehouse architecture, ensuring multidisciplinary data integration. This layer enables the aggregation of information from various sources across the enterprise into a unified analytical environment. Using OLAP technologies, multidimensional analyses are conducted-such as what-if analysis, scenario modeling, and drill-down exploration-to support dynamic decision-making.

At the next stage, Model-Based Analytics processes are applied. Within this layer, optimization, simulation, and forecasting models are developed. Following this, Artificial Intelligence (AI) and Machine Learning (ML) components are integrated to perform advanced analytical tasks, including prediction, classification, and decision-tree modeling.

All these data and analytical outputs are presented in the Information Presentation and Visualization layer through interactive dashboards, reports, and visual analytics tools, allowing users to dynamically explore the data according to various scenarios.

Ultimately, the insights generated by this architecture serve decision-makers across different organizational levels. Strategic management utilizes them to shape long-term policies and investment decisions; tactical management applies them to resource allocation and medium-term planning; and operational management leverages them in daily decision-making processes through BI

support. In addition, expert analysts, policy makers, and regulatory bodies can use the DSS architecture to conduct systematic and evidence-based analyses. Furthermore, rule-based or AI-driven automated decision engines can act upon these insights, directly influencing operational outcomes.

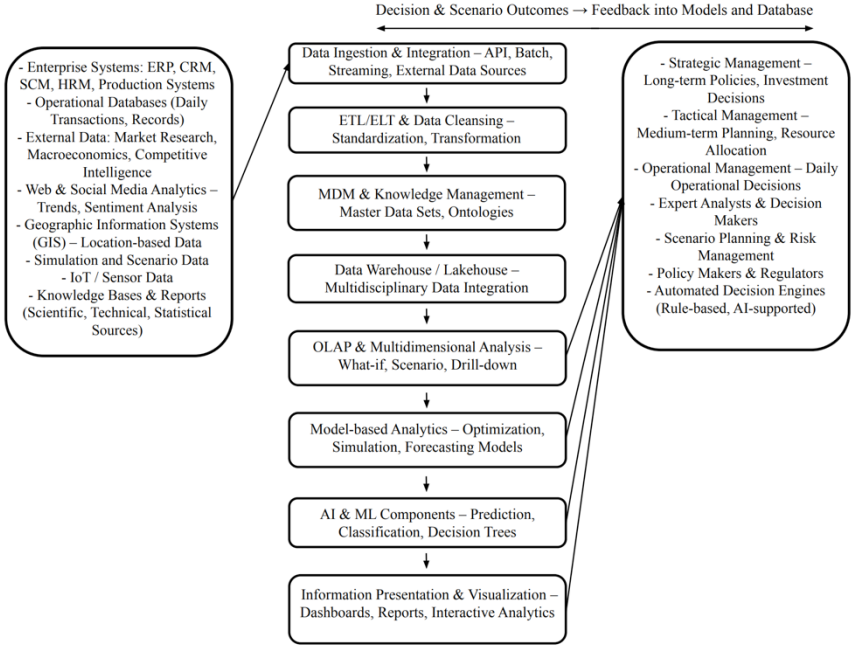


Figure 6. Layers of Business Intelligence Architecture for Decision Support Systems

Thus, the BI architecture based on DSS integrates organizational, environmental, and technological data to enable managers to make accurate, rapid, and flexible decisions. This structure not only evaluates past performance but also anticipates future scenarios, making tangible contributions to strategic planning, risk management, and resource optimization processes.

5. Conclusion

The convergence of BI and MIS represents a pivotal transformation in how organizations generate, interpret, and utilize information for strategic advantage. Throughout this chapter, BI has been examined not merely as a technological tool but as a strategic management architecture-one that unites data, analytics, and decision-making within a unified organizational framework.

Integrating BI architectures into core MIS domains such as CRM, SCM, ERP, and DSS enables organizations to transcend traditional reporting functions and embrace predictive, prescriptive, and autonomous decision environments. The layered BI structures-encompassing data ingestion, ETL processing, warehousing, OLAP analysis, and advanced analytics-create an end-to-end ecosystem where data evolves into intelligence and intelligence into action.

This integration redefines managerial processes by fostering real-time insight generation, enhanced transparency, and agility in responding to environmental volatility. Organizations that leverage BI-MIS integration are no longer limited to retrospective analysis; they can simulate future scenarios, optimize resource allocation, and institutionalize a culture of continuous learning and adaptation.

From a strategic standpoint, the BI-MIS relationship extends beyond operational efficiency-it contributes to organizational resilience, sustainability, and innovation capability. As AI, machine learning, and automation technologies continue to advance, BI architectures will increasingly function as adaptive, intelligent systems capable of self-learning and dynamic decision optimization.

In essence, this chapter has demonstrated that the real value of BI lies not only in processing information but in shaping the very cognitive infrastructure of organizations-turning data into foresight, complexity into clarity, and uncertainty into strategic opportunity.

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