

## CHAPTER 2 - LITERATURE REVIEW

The industrial landscape has experienced substantial transformation since the First Industrial Revolution. From the introduction of steam power to the emergence of automation and computing technologies, each period has contributed to major technological progress. At present, the world is entering the Fourth Industrial Revolution (Industry 4.0), defined by the integration of cyber-physical systems, the Internet of Things (IoT), and interconnected digital networks.

Despite ongoing advancements, many companies—including Company XYZ Indonesia—remain in the process of shifting away from Industry 3.0 practices and working toward full digital integration. This transition presents both challenges and opportunities, especially for industrial engineering firms that have traditionally prioritized technical products and services over data-driven, customer-oriented strategies. To remain competitive in the digital era, such firms must leverage information technology—particularly business intelligence tools—to enhance their understanding of operations and support more effective analysis and optimization.

This chapter reviews the literature related to logistics performance improvement through the integration of data governance, process optimization, and business intelligence within the framework of Industry 4.0. It addresses the limitations of conventional logistics decision-making, which often relies on fragmented data and manual practices. The chapter also emphasizes the importance of leveraging governed data, simulation models, and BI tools to support cost reduction and delivery time improvement. For industrial companies like Company XYZ Indonesia, these capabilities are essential to enable data-driven operational visibility and continuous improvement across logistics functions.

### 2.1. Industry Transformation 4.0

The First Industrial Revolution (Industry 1.0) began around 1784, primarily in Western Europe and the emerging United States, with Britain playing a central role. This period

was characterized by the introduction of steam power, mechanized production systems, and innovations such as the mechanical weaving loom, which significantly transformed manufacturing processes. The second industrial revolution (Industry 2.0) started around 1870 in cities like Detroit and Chicago, introducing mass production, assembly lines, and the electrical industry. By 1969, the third industrial revolution (Industry 3.0) commenced, characterized by automation, computers, and electronics transforming industries. In the present day, we are in the midst of the fourth industrial revolution (Industry 4.0), which emphasizes cyber-physical systems, the Internet of Things (IoT), and networks.

Industries must adapt to information technology, including industrial engineering firms like Company XYZ Indonesia, to stay competitive. By leveraging information technology through the application of business intelligence combined with data analytic from the availability of internal data, companies can better understand customer data to sustain and enhance their growth and firm performance.

Data is crucial for a company's potential growth, but it is often underutilized. While data provides insight into past performance, it does not automatically guide future decisions. By analyzing the data, companies aim for faster growth. Using a comprehensive database improves the decision-making process by offering better insights. To visualize data effectively, companies need specific tools, methods and expertise to turn data into actionable decisions.

## **2.2. Company XYZ Overview**

Company XYZ is a global leader in technical products and services for Positive Displacement Pump and System sector, with a strong presence in Indonesia since 2011. Headquartered in Germany, the company operates more than 50 offices worldwide, including one in Jakarta, Indonesia.

Currently, Company XYZ offer 4 Pump technology and provides solution to industrial customer across 5 focused business fields. These fields are divided as follows: F+P (Food and Pharmaceutical), C+P (Chemical and Pulp & Paper), E+E (Environmental

and Energy), and O+G (Oil and Gas). Additionally, Company XYZ Indonesia focuses only on the technical engineering solutions and distribution for pump and systems, while all production of the goods is manufactured on the global factory at German, Brazil, Spain, China, India and assembly center at Bangkok, Thailand.

Company XYZ is exploring the possibility of establishing a manufacturing facility in Indonesia by the fiscal year 2027 (BY27). This initiative is part of the company's strategic expansion within the SEAO (South Asia, Australia, and Oceania) region, which includes operations in Singapore, Malaysia, the Philippines, Thailand, Vietnam, and Australia.

Company XYZ operates on a fiscal year basis, beginning on July 1st and ending on June 30th of the following year. Thus, BY25 refers to the business year starting on July 1, 2024, and ending on June 30, 2025.

Figure 2.1. show the organizational structure of the logistic Department at Company XYZ Indonesia

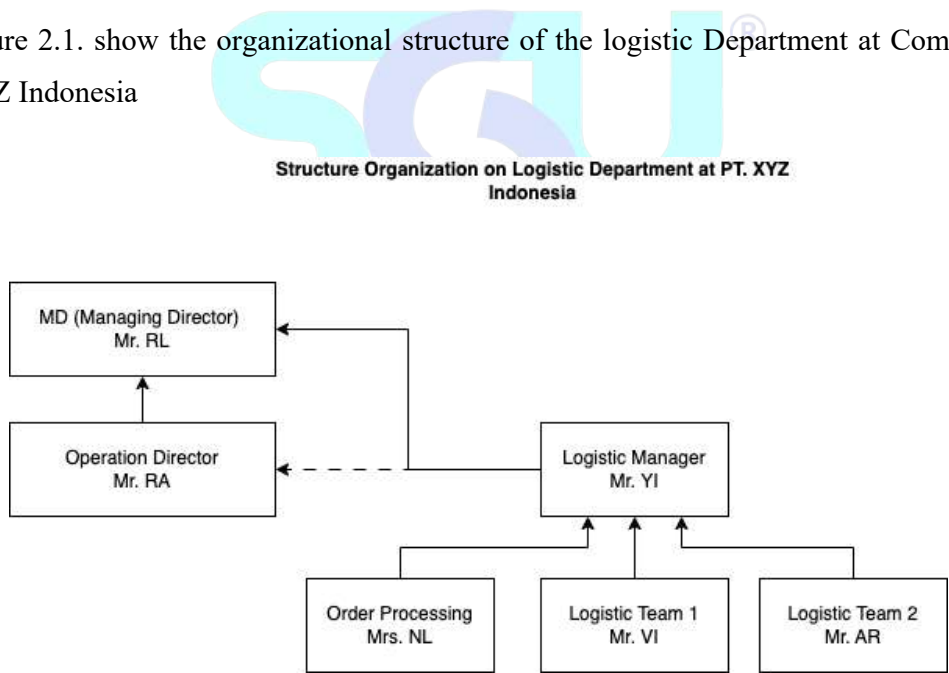


Figure 2. 1. Organizational Structure of the Logistic Team - PT. XYZ

Figure 2.1 illustrates the organizational structure of the Logistics Department at PT. XYZ Indonesia. The Managing Director (MD) serves as the head of the company, to whom the logistics team reports all activities. Additionally, the Logistics Department

reports its operational matters to the Operating Director, who also acts as the Change Manager responsible for driving process optimization across PT. XYZ Indonesia's operations.

In terms of visualization tools, Company XYZ provides Microsoft 365 access to all employees, making Microsoft solutions the standard platform for communication, reporting, and data visualization. However, the current utilization is limited. Most departments primarily use Microsoft Office applications (Word, Excel, and PowerPoint), OneDrive, and SharePoint mainly for communication and document sharing. At present, only the Finance Department actively uses Power BI, and its usage is limited to financial reporting purposes.

### **2.3. Logistic Management and International Trade**

Trade and logistics management is a critical component of supply chain operations, ensuring the planning, implementation, and control of the efficient flow of goods, services, and information from the point of origin to the point of consumption. In engineering trade industries, logistics complexity increases due to the technical nature of products, stringent delivery timelines, and customer expectations for cost effective solution. Effective logistics management directly impacts a firm's ability to balance operational costs, delivery accuracy and pricing competitiveness as key factors for sustaining profitability in the global market (Lee et al., 2022).

In trade and logistics term, there are Incoterms which are standardized by the International Chamber of Commerce (ICC), define the responsibilities of buyers and sellers in international trade, clarifying risk, costs, and delivery obligation (ICC, 2019). The incoterm 2020 framework, the latest revision, categorized 11 terms. For example FOB, CIP, DAP, DDP, that determine how logistic costs and risk are allocated between parties (Bergami and Tichá, 2022).

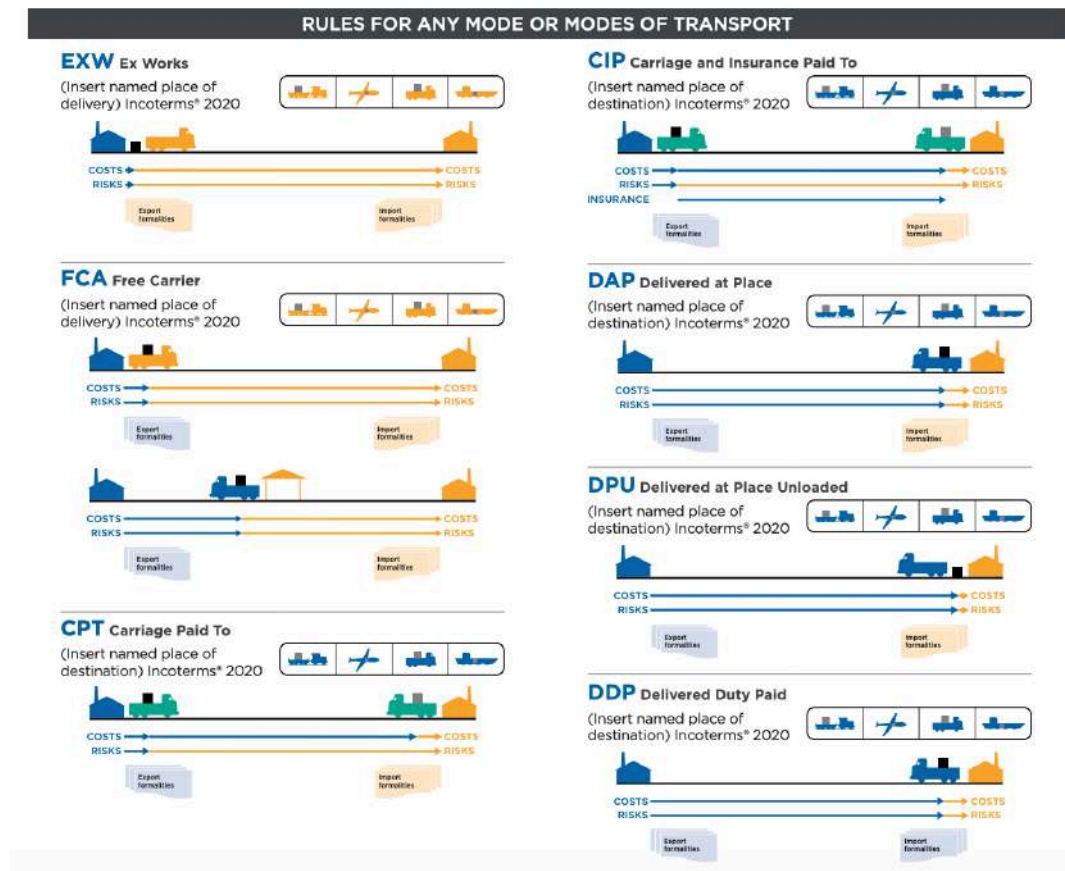


Figure 2. 2. Incoterms 2020 by ICC (ICC, 2019)

Figure 2.2 explains the rules for any mode or modes of transportation related to the cost, risk, and the insurance responsibility between the parties, helping to mitigate the responsibility between supplier and customer. For example, the DDP (Delivery Duty Paid) incoterm, common incoterm used by company XYZ Indonesia as a seller to the buyers, stipulates that the seller assumes all costs and risk associated with delivering goods to the buyer's specified location. This comprehensive responsibility includes several cost components that the company XYZ must manage.

Incoterms, or International Commercial Terms, are globally recognized standards that define the responsibilities of buyer and sellers in international trade, particularly concerning the delivery of goods. A clear understanding of these terms is essential for

organization to conduct accurate cost analysis and make informed comparisons between different trade agreements.

Table 2. 1. Data influence on trade logistic cost.

| Cost Components                      | Description                                                                           |
|--------------------------------------|---------------------------------------------------------------------------------------|
| Supplier's Workshop Cost             | Expenses incurred at the supplier's facility for preparing the goods for shipment.    |
| Inland Transportation to Origin Port | Costs for transporting goods from the supplier's location to the port of departure.   |
| Port Storage at Origin               | Fees for storing goods at the port before they are loaded onto transport vessel       |
| Freight Cost                         | Charges for transporting the goods (land, sea, or air) to the destination country.    |
| Handling Cost at Destination Port    | Expenses related to unloading and handling goods upon arrival at destination port     |
| Storage at Destination Port          | Costs for storing goods at the destination port before they are cleared for delivery. |
| Taxes at Destination Country         | Duties and taxes imposed by the destination country, which the supplier must pay.     |
| Local Transportation to customers    | Costs for delivering goods from the destination port to buyer's location              |
| Other expenses                       | Costs expenses for labor, re-packing, Quality check, etc.                             |

Table 2.1 explains the cost components influenced by data in international trade based on the DDP (Delivery Duty Paid) (ICC, 2019).

According to the World Bank's 2023 Logistics Performance Index (LPI), Indonesia ranked 63rd out of 139 countries, reflecting a notable decline of 17 positions from its previous rank of 46th in 2018. Singapore achieved the top global ranking, while Malaysia and Thailand were positioned at 31<sup>st</sup> and 37<sup>th</sup>, respectively (World Bank, 2023). This decline highlights that Indonesia's logistics costs remain high and underperforming compared to other ASEAN nations.

According to (Mešić et al., 2022), the LPI is influenced by six key components: customs, infrastructure, ease of arranging international shipments, quality of logistics services, tracking and tracing, and timely delivery of shipments. In their study Mešić's evaluated the logistics performance of Western Balkan countries using the CRITIC-MARCOS model, which involves five steps: data preparation, analysis of LPI values, calculation of weight values using CRITIC, ranking countries with MARCOS, and conducting sensitivity analysis. This methodology enabled the identification of the most efficient logistics performer among the evaluated countries.

Additionally, a study by Chia Nan Wang employed fuzzy analytic methods to address uncertainty in decision-making, leading to unsustainable third-party logistics selection (Wang et al., 2021)

In the context of PT. XYZ Indonesia, internal data reveals that logistics costs are notably high, constituting 14% of annual sales costs. This is significantly higher compared to XYZ's operations in Singapore, Malaysia, and Thailand, where logistics costs average below 10%.

#### **2.4. Business Intelligence (BI)**

Business intelligence (BI) tools play a key role in this process, these tools help companies create dashboard that present essential information clearly, making it easier to make quick and informed decisions (M. A. Khan et al., 2020).

Business intelligence improves efficiency of decision-making in company operations, helping to make business more competitive and sustainable (Kongthanasuwan et al., 2023). Company needs to create the business intelligence dashboard to help

management to understand the data. Nowadays, most industrial engineering companies in Indonesia like company XYZ still use conventional method – human knowledge for decision-making. In the era of Industry 4.0, the company needs to adopt information technology based on data analytics, and conduct feasibility study to use the available data more powerfully, helping the company grow.

Industrial engineering often relies on tacit knowledge for making decision, which is passed on by senior staff leading inconsistent decisions. A business intelligence dashboard is needed to visualize the available data and make it easier for management to make decisions. While business analytics employs historical data to gather insights and carry out company operations to drive customer requirements and boost productivity, business intelligence uses both current and historical data. Data is meaningless without processing and analysis (Niu et al., 2021).

To integrate the data analytics with business intelligence tools, the framework by (Ranjan, 2009) and also has also has been discussed in the current study for market analysis at brake pad manufacturing company in Thailand by (Kongthanasuwan et al., 2023) show at figure 2.3:

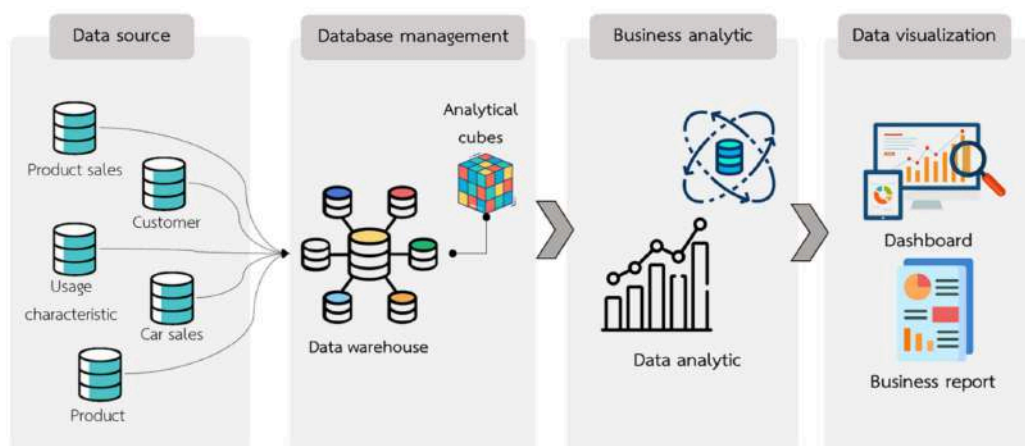


Figure 2. 3. Business Intelligence Architecture (Kongthanasuwan et al., 2023)

Figure 2. 3. shows the business intelligence architecture, focused on how to use data to and be transformed into data visualization through data source, database management, business analytics and the last is data visualization.

Integrating data analysis with business intelligent study by Dong Hui Jin, emphasize the critical role of integrating data analysis with business intelligence (BI) to maintain competitiveness and ensure sustainable growth for companies (Jin and Kim, 2018). The research utilizes a DBA framework in conjunction with BI, transforming raw logistic data into valuable insights. This approach identifies the types and scopes of data collection based on specific logistic areas, potentially enabling small enterprises to evolve into large corporations or market leaders by leveraging meaningful information derived from data analytics (Jin and Kim, 2018). In line with this, Heba Hatamlah emphasize the critical role of big data analytics (BDA) in addressing the volatility of supply and demand, as well as the growing need for more tailored goods and services. To effectively respond to these challenges, firms must implement advanced BDA processes and procedures that enable the extraction of meaningful insights from complex datasets. These insights support improved decision-making and contribute to the optimization of supply chain and logistics operations (Hatamlah et al., 2023).

Table 2. 2. Strengths and Weakness of BI Framework

| Framework                                                                      | Strengths                                                                                                                                                                                                                                   | Weaknesses                                                                                                                                                             |
|--------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Business intelligence Architecture, the study by (Kongthanasuwan et al., 2023) | <p>+ The framework enhances decision-making. BI architecture facilitates faster and more accurate reporting.</p> <p>+ The BI system streamlines data preparation process, resulting increase efficiency by reducing the time and effort</p> | <p>- Needs continuous adaptation, as business environments evolve, BI architecture must be updated and adapted. The framework dost not include the data lifecycle.</p> |

| Framework | Strengths                                                                    | Weaknesses |
|-----------|------------------------------------------------------------------------------|------------|
|           | required to collect the data and analyze the data.                           |            |
|           | + The architecture supports the development of dashboards and visualization. |            |

Table 2.2 summarizes the strengths and weaknesses of the Business Intelligence (BI) Architecture framework, as outlined by (Kongthanasuwan et al., 2023). The study highlights the framework’s significant advantages in enhancing organizational decision-making, particularly through improved data reporting capabilities. By enabling faster and more accurate reporting, the BI system supports timely and informed decision-making processes. Additionally, it streamlines data preparation by reducing the time and effort needed to collect and analyze data, thereby contributing to overall operational efficiency. A further strength of the framework lies in its ability to support dashboard and visualization development, which is essential for communicating insights clearly to key stakeholders.

Despite its advantages, the BI Architecture framework also presents several limitations. A primary concern is the requirement for continuous adaptation, as dynamic business environments demand that BI systems be frequently updated to maintain their relevance and effectiveness. Furthermore, the framework does not fully address the complete data lifecycle, which may result in issues related to data consistency, integrity, and long-term usability. These limitations underscore the importance of integrating BI initiatives with a comprehensive data governance strategy to ensure sustained performance and data reliability across organizational functions.

#### 2.4.1. Microsoft Power Automate, PowerApps, Power BI and SharePoint.

Microsoft Power BI is a business analytics platform developed to provide interactive visualizations and business intelligence through an intuitive interface that enables users to build customized reports and dashboards. One of its core strengths lies in its ability to convert raw data into actionable insights. As noted by (Kongthanasuwan et al., 2023), Power BI has been successfully implemented in the automotive industry in Thailand, where its data visualization features support market analysis and marketing planning. Beyond this sector, Power BI has also demonstrated versatility through its applications in finance, healthcare, and gaming industries. Its flexibility and broad functionality make it suitable for various data-driven environments. In the context of this study, Power BI is explored further in conjunction with supporting frameworks to enhance logistics performance monitoring and operational decision-making. It explores the potential for future studies on its implementation in various industries and examine whether its use requires minimal IT expertise, with simple dashboards aiding significant growth in industrial engineering companies.

To automate correcting data and issue, Power BI can also be integrated with other database, file and web services. Additionally, Power BI automatically refreshes data with updated information and ensure security when publishing report created within the company. Power BI features a gateway that enables connectivity to SQL server database, it can also consolidate all the company data whether it is stored on-premises or in the cloud.

Previous studies have emphasized the significant impact of Business Intelligence (BI) systems, supporting strategic decision-making processes in various industries (Abu-AlSondos, 2023)(Kongthanasuwan et al., 2023). These systems provide valuable insights through data visualization, BI management, and data quality, ultimately leading to improved decision-making quality (Abu-AlSondos, 2023). Additionally, the use of BI tools like Power BI has been recognized for their ability to integrate data, analyze information, and provide real-time updates, supporting agile decision-making processes crucial in today's competitive business environment (Gonçalves et al., 2023).

By leveraging Power BI's capabilities, engineering firms can strengthen their logistics strategies through data-driven decision support, enabling informed and timely actions based on accurate operational insights.

Reducing operational costs remains a key priority for logistics managers. The adoption of Microsoft Power Apps in logistics operations has emerged as a transformative approach, particularly within manufacturing and trade sectors. By leveraging low code development, Power Apps enables organization to create customized applications tailored to specific needs, enhancing operation efficiency and reducing cost (Biedova et al., 2023).

#### 2.4.2. SDLC (Software Development Life Cycle)

Engineering companies increasingly adopting low-code platforms like Microsoft Power Apps and Power Automate to streamline application development and improve project delivery performance. Recent studies highlight that low-code development can significantly accelerate delivery timelines and reduce costs (Martinez and Pfister, 2023). By integrating these tools within the traditional Software Development Life Cycle (SDLC), organizations aim to monitor and optimize delivery time and cost for engineering logistics. This integration often involves adapting SDLC phases, from planning and design through deployment to accommodate rapid, iterative development and automation workflows. Case studies indicate that such adaptations result in faster application deployment and measurable cost savings, while maintaining quality standards and control (Martinez and Pfister, 2023).

Low-code platforms have reshaped traditional Software Development Life Cycle (SDLC) by enabling greater involvement of non-developers (domain experts) and by shortening development iterations. Instead of a lengthy requirements phase followed by extensive coding, Power Apps provides a visual design environment where engineering domain experts and developers co-design applications via drag-and-drop dashboards, reducing misunderstandings and rework (Shi et al., 2025). This collaborative "fusion development" approach aligns with Agile principles and has been

shown to reduce requirement misalignment in manufacturing case studies (Shi et al., 2025).

In logistics environments, where delivery timelines and cost control are critical, the integration of Microsoft Power Apps and Power Automate offers a low-code approach to enable rapid development and automation of tracking and monitoring solution. The choice of a suitable SDLC model is critical to ensure that such tools are delivered effectively, with strong stakeholder collaboration, cost control, and adaptability to automation requirements. The following section provides a focused overview of four commonly used SDLC approaches—Waterfall, Iterative, Agile, and Rapid Application Development (RAD)—evaluated in the context of low-code development for logistics operations.

Waterfall is a traditional, linear SDLC model where each phase: requirements, design, implementation, testing, and deployment is completed sequentially. It is best suited for projects with fixed, well-understood requirements (Olorunshola and Ogwueleka, 2022). However, for logistics operations where processes often evolve and rapid delivery of insights is essential, Waterfall's rigidity becomes a limitation. It lacks flexibility to accommodate feedback or integrate new features mid-cycle, which delays deployment of valuable updates like delivery alerts or cost thresholds via Power Automate. Thus, while Waterfall ensures thorough documentation and structure, it is less suitable for dynamic Power Apps development, especially when rapid response to operational changes is required (Mokhtar and Khayyat, 2022).

Iterative development divides the software into manageable components and delivers them in repeated cycles or “iterations.” Each iteration includes planning, design, implementation, and evaluation, allowing developers to refine the solution over time. This model provides earlier partial implementations than Waterfall and enables feedback at regular intervals. For logistics applications in Power Apps, such as delivery time dashboards or cost tracking workflows, iterative development ensures continuous progress and stakeholder visibility. However, the need to wait for the next cycle to address changes may limit agility compared to Agile, though it remains a practical

option when some degree of upfront planning is still preferred (Mishra and Alzoubi, 2023)

Agile emphasizes rapid, incremental development with active user participation and flexibility to adapt requirements throughout the project. This model aligns closely with Power Apps development, which thrives on user feedback and evolving needs. Agile's sprint-based approach allows logistics teams to release a functional delivery monitoring feature quickly, test it in the field, and iteratively improve it based on feedback. It also supports the gradual addition of Power Automate flows for automation (e.g., late shipment notifications or cost alerts). Agile has proven highly effective in logistics and supply chain settings where speed and collaboration are crucial (Bhattacharyya and Kumar, 2023) (Mishra and Alzoubi, 2023)

Rapid Application Development (RAD) focuses on fast prototyping and intensive end-user engagement, making it well-suited for Power Platform projects. RAD allows logistics teams to quickly develop a proof-of-concept for monitoring tools using Power Apps and iterate on it based on continuous input from users such as warehouse managers or dispatchers. It is particularly valuable when requirements are unclear or expected to change, and time-to-value is critical. While RAD promotes quick delivery and adaptability, it requires disciplined project governance to avoid scope creep or technical debt. When supported by a strong team and proper lifecycle management, RAD can lead to efficient, user-aligned logistics solutions (Q. F. Khan et al., 2020)

## **2.5. ODM-BDA (Optimized Data Management using Big Data Analytics)**

The study by (Niu et al., 2021), explores the integration of big data analytics into business intelligence (BI) and its implication for decision-making processes within organization. It is designed to convert unstructured data into actionable insights that can inform policy decisions and boost business efficiency and productivity. The research includes case studies of organizations that have successfully implemented big data analytics, illustrating the practical application of the data methodologies discussed.

The study proposes the ODM-BDA framework as a structured approached to enhance organizational effectiveness and decision-making. The framework includes several critical components, such as:

1. Data Collection and Management. It emphasizes the importance of gathering and managing large volumes of data from various sources, including cloud services, to ensures comprehensive analysis.
2. Analytical Services, the framework is designing analytical services that focus on supply chain management (SCM), marketing analysis, sales analysis, and servicing analysis, which are essential for understanding customer behavior and improving business strategies
3. Performance Matric: The ODM-BDA framework is evaluated based on performance metrics such as accuracy, efficiency, precision, and error rate. the experiment result indicates a high accuracy ration of 96.1%, efficiency ratio of 97.2% and low error rate of 0.66% in experimental result.

Table 2. 3. Result of the implementing ODM-BDA framework for effectiveness of decision-making on case study.

| Performance Matric | Result Ratio Rate |
|--------------------|-------------------|
| Accuracy           | 96.1%             |
| Efficiency         | 97.2%             |
| Precision          | 96.3%             |
| True Positive rate | 80.6%             |
| Error rate         | 0.66%             |
| Delay Rate         | 52.8%             |

As we can see in table 2.3. the result indicate that the ODM-BDA framework significantly enhance organizational decision-making capability through improved accuracy, efficiency, and reduce error rates, making it a valuable tool for business leveraging big data analytics.

Beside the result of high accuracy and efficiency ratio, this framework also has some weak points that can be identified. One of the significant challenges highlighted is related to the data privacy and data protection. The paper acknowledges that despite the benefits of big data analytics, there are difficulties regarding privacy and protection, which can hinder organization from fully leveraging these technologies. This concern may limit the applicability of the proposed framework in sensitive environment where data security is paramount. This paper also mention that large-scale analytics is still in its “infantile stage” indicating that the field is not fully matured. This suggests that the framework proposed may not be robust enough to handle the complexities and evolving nature of big data analytics effectively. This immaturity can lead to uncertainties in the frameworks long-term viability and effectiveness. The cost and resources requirement for the development of business intelligence big-data is noted to be costly and significant computer resources requirement. This can be a barrier for smaller organization of those with limited budgets potentially restricting the framework’s accessibility and widespread adoption.

Table 2. 4. Strength and Weaknesses of ODM-BDA Framework

| Framework                                  | Strengths                                                                                                                          | Weaknesses                                                                                                                                                                                                                        |
|--------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| ODM-BDA, the study from (Niu et al., 2021) | + Hight performance metric. Impressive performance metric including accuracy ratio of 96.1% and error rate 0.66%                   | - Privacy and security concern. The framework potential issues related to privacy and data protection.                                                                                                                            |
|                                            | + The framework is designed to improve organization decision-making by utilizing big data analytics, it helps organization convert | - Cost and resource limitations, the implementation of ODM-BDA framework required significant financial and computation resources, which can be barrier for small organization. The hight cost associated with big data tools and |

| Framework | Strengths                                                                                                                    | Weaknesses                                             |
|-----------|------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------|
|           | unstructured data into actionable insights.                                                                                  | infrastructure can restrict access to the framework    |
|           | +Comprehensive performance Evaluation, the framework includes a performance evaluation process, measuring various parameter. | - Limited study for the theoretical ODM-BDA framework. |

Mentioning on table 2.4 is strength and weakness of the ODM-BDA, highlighting that accuracy ratio on performance matrix of 96.1% and error rate 0.66% based on study by Niu, but in other hand, the cost and resource also considered high.

## 2.6. CRISP-DM (Cross-Industry Standard Procedure for Data Mining)

CRISP-DM is recognized as the de facto standard for applying data mining project. It is widely accepted in the field of data mining, indicating that it serves as a foundational framework for practitioners and researchers alike. The study by (Schröder et al., 2021) explores CRISP-DM process model and can be described as below table 2.5. CRISP-DM process description

Table 2. 5. CRISP-DM Process Description

| Phase                  | Short description                                                                                                                                                                                                                                 |
|------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Business Understanding | Explore business objective from business perspective, to understand the business situation for available resources of data, problem, goals and describe current solution and company expectation to leverage the business intelligence dashboard. |
| Data Understanding     | Collecting and exploring the existing data and describing it. Checking the data quality is crucial in this phase. Verifying data                                                                                                                  |

| Phase            | Short description                                                                                                                                                                                                                   |
|------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
|                  | quality, audit the data and look for missing data, data error, and standardization of the data.                                                                                                                                     |
| Data Preparation | Data preparation is the most important and time-consuming. Data selection should be conducted. Bad data quality can be handled by data cleaning. Constructing new data, integrating data and reformatting data into specific needs. |
| Evaluation       | During the evaluation stage, the result is compared with the company objective.                                                                                                                                                     |
| Deployment       | The deployment of the user guide/procedure. It could be a final report/procedure of business intelligence dashboard. The user guide includes planning, monitoring, and maintenance.                                                 |

Table 2.5. show the process description of CRISP-DM framework. The short description for every step on the CRISP – DM framework starting from business understanding, Data understanding, Data Preparation, Modelling, Evaluation, also deployment.

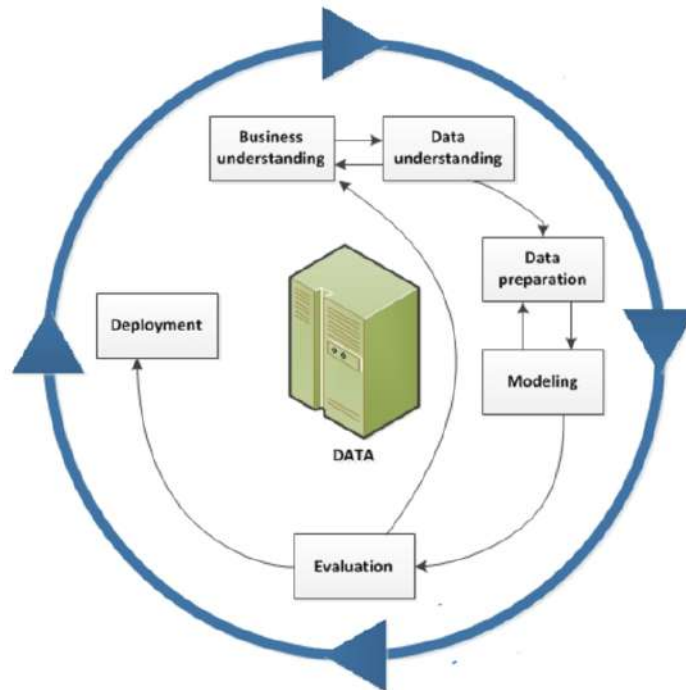


Figure 2. 4. The data mining life cycle by CRISP-DM (Schröder et al., 2021)

Figure 2.4. Illustrates the data mining life cycle according to the CRISP-DM model, where the arrow represents the process flow, if the data quality is found to be insufficient during the data understanding phase, the process can revert to business understanding phase to gather more information about the data usage, aiding subsequent steps.

Another study by (Brzozowska et al., 2023) and (Massmann et al., 2020) also delves into data engineering within the framework on the CRISP-DM Model for production data analysis, aiming to enhance organizational decision-making by employing data mining technique for predictive analysis and management. its focuses on the initial three phases of the CRISP-DM Model. Business Understanding, Data Understanding, and Data Preparation, specifically in the context of small batch production. The study's primary objective is to adapt the CRISP-DM model to predict assembly cycle time, a crucial factor in production planning and resource allocation. Through the integration of data engineering principles with the CRISP-DM model, this research aims to enhance decision support system and forecasting accuracy in manufacture environments.

Table 2. 6. Strengths and Weakness of CRISP-DM Framework

| Framework                                       | Strengths                                                                                                                             | Weaknesses                                                                                                   |
|-------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------|
| CRISP-DM, the study from (Schröer et al., 2021) | + CRISP-DM is recognized as an industry independent process model, making it applicable across various industries.                    | - Limited focus on deployment and primary goals. The lack of emphasis on deployment phases.                  |
|                                                 | + The framework provides a standardized approach which can help streamline process within data science team.                          | - The paper only coverage short period of time review, which may limit the comprehensiveness of the finding. |
|                                                 | + Identify the best systematic and structured process phase.                                                                          |                                                                                                              |
|                                                 | + The development of the initial classification framework during the review process allows for continuing adjustment and improvement. |                                                                                                              |

Table 2.6 presents the strengths and weaknesses of the CRISP-DM (Cross Industry Standard Process for Data Mining) framework, based on the study from (Schröer et al., 2021). A key advantage of the CRISP-DM framework is its industry-independent nature, allowing it to be applied across a wide range of sectors. This adaptability makes it a valuable reference model for organizations pursuing data mining or data analytics initiatives. The framework provides a standardized and structured methodology that promotes collaboration and clarity within data science teams. It also aids in identifying well-defined process phases, contributing to improved project consistency and

transparency. Moreover, the initial classification system developed during the review stage facilitates continuous refinement, allowing the methodology to evolve and remain effective in dynamic business environments.

On the other hand, the CRISP-DM framework has certain limitations. It places limited emphasis on the deployment phase, which is a crucial stage for ensuring that data-driven solutions are effectively implemented in business operations. This lack of focus may hinder the realization of full business value from analytical projects. Additionally, the referenced study only covers a short review period, which may restrict the depth and breadth of the insights gained. These weaknesses highlight the importance of supplementing CRISP-DM with additional practices or frameworks that address deployment and long-term monitoring to ensure comprehensive and sustained impact.

## **2.7. Data Governance, Data Management, and Data Architecture**

Organization is increasingly using Data analytic as initiative to support decision making on their operations. However, the accuracy of the output heavily depends on the quality of the input data. Improving data quality is key. Organization produce massive amount of data, which should be valuable for the business. However, data governance may still face many challenges, especially for the organization focused on the product quality, such as Company XYZ Indonesia.

Data Governance (DG) is broadly defined as a system of decision rights, processes, standards, and policies that ensure data is managed as a valuable asset in an organization (Li et al., 2024). In essence, Data Governance establishes who is accountable for data quality and usage, what rules and standards apply to data, and how those rules are enforced. A core goal of data governance is to enable effective, efficient, and compliant use of data across the enterprise (Bližnák et al., 2024). For example, the DAMA-DMBOK defines DG as “the exercise of authority, control, and shared decision-making (planning, monitoring, and enforcement) over the management of data assets,” with the aim of managing data as a strategic asset and formalizing data policies and procedures (Li et al., 2024). Key elements of DG include establishing data ownership and stewardship roles, defining data quality standards, ensuring regulatory compliance and

aligning data initiative with business strategy (Abraham et al., 2019). Recent studies stress that DG is *essential* for companies to maximize the value of their data in a safe and cost-effective manner (Bližnák et al., 2024), especially as data volume and complexity grow in the era of analytics and artificial intelligence.

The literature highlights several best practices for successful data governance, many of which are particularly relevant to logistics and supply chain operations. A fundamental principle is to treat “data as an enterprise asset” that has value (and cost) similar to physical inventory (Li et al., 2024). This mindset underpins investment in data quality and integration initiatives. Another critical practice is implementing a cross-functional governance framework – given that logistics data spans multiple departments and often multiple organizations, governance must involve stakeholders from across these units (Li et al., 2024). Cross-functional DG committees or councils can set unified policies for data standards and resolve ownership issues across silos. Closely related is the importance of assigning clear roles and responsibilities for data (data owners, data stewards, custodians) so that accountability for data quality and timeliness is established (Bližnák et al., 2024).

In the context of logistics, effective DG helps ensure that all parties handle data consistently – for instance, defining standard codes for products and locations, or agreeing on data-sharing policies with suppliers. Data quality management is often cited as a cornerstone of DG: ensuring that key logistics data (e.g. inventory levels, shipment statuses, customer orders) are accurate, complete, and timely. High data quality is crucial for reliable supply chain analytics and operational decisions. A recent systematic review by Bernardo *et al.* (2024) notes that data, when properly governed, becomes a “hidden weapon” for decision-making and competitiveness (Bernardo et al., 2024). They emphasize that strong data governance, coupled with technology utilization, significantly contributes to maximizing enterprise value. Another study in the Operations and Supply Chain Management domain underscores that DG provides the “*right people with the right information at the right time*” by enforcing authority and control over data assets (Li et al., 2024).

2.7.1. DAMA- DMBOK (Data Management Body of Knowledge)

Industrial and trading firms often face data governance (DG) challenges such as siloed data systems, lack of transparency in data lineage, and difficulty enforcing standards across legacy platforms. A case study by Sigi (2024) at an Indonesian industrial company (PT XYZ) illustrates common issues: unclear data ownership and insufficient governance led to inconsistent data sources and delays of up to three days in compiling logistics reports (Sigi, 2024). Data had to be manually gathered from disparate systems, indicating poor integration. Introducing a formal data governance framework (DAMA-DMBOK in that case) was recommended to create a well-organized data management structure and eliminate these inefficiencies. This example demonstrates how robust DG can directly support logistics operations by improving data integration and decision speed.

Data governance focuses on authority and control over data assets through defining roles and responsibilities, monitoring compliance, ensuring data accountability and policy or guidelines setting. While data management focuses on execution and operation of data-related processes as seen on figure 2.6. The essential concept of Data Governance and Data management are shown on figure 2.5:

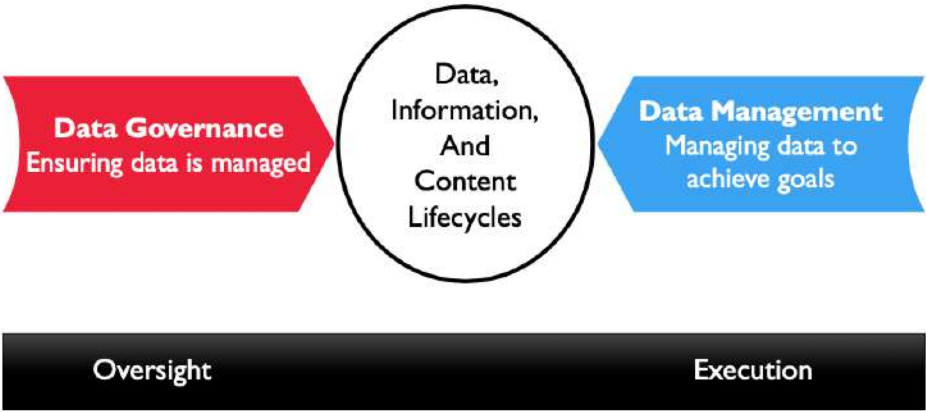


Figure 2. 5. Essential Concepts of Data Governance and Data Management (Henderson et al., 2017)

Figure 2.5. draw the essential concept of data governance and data management, while data governance is to oversights ensuring data is managed, and data management as execution to managing data to achieve goals.

Data management is a broad discipline encompassing the policy, process, and technology used to manage information through its lifecycle. Data often unmanaged, and aiding organization failed to fulfill the organization needs for decision making across a variety of business operation. Organization often overlook the significant of data management (Sigi, 2024) which in fact demands serious consideration.

DAMA DMBOK framework introduces 10 (ten) focus area of data management as seen on Figure 2.6, data governance is a component of data management that provide a functional approach to build robust data governance within organization.

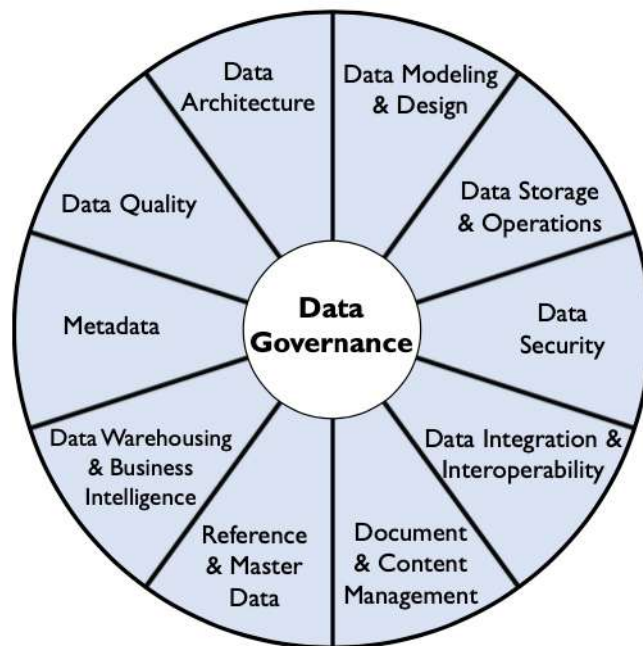


Figure 2. 6. DAMA -DMBOK2 Data Management Framework (the DAMA Wheel)  
(DAMA International, 2017)

DANA – DMBOK as shown at figure 2.6. focusing on 10 (ten) areas as mentioned on the figure 2.6, before creating Data Governance, the organization need to really check

the maturity level on the 10 area. Collecting appropriate input for assessing the maturity level could also from FGD (Forum Groups Discussion) by looking for the available data provided by the organization. The planning communicates with stakeholder before the assessment to ensure their engagement and overall business objective.

From the FGD, assessment of maturity level gets the result of the organization capability, and the organization may able to focus on the area that more important and reliable for the company.

According to paper by (Raptis et al., 2019) data management including data collection to its process, and categorize it into 3 (three): data presence, data coordination, and data computation. This focusing on data collection, preprocess, storage, and data processing. The study by (Freitas et al., 2025) on the research literature review of data management in industry, the authors provide the concept overview for data management, including data management, big data, data storage, data extraction, data preprocessing, data The study highlights the importance of data management in industrial environment due to increasing volume of big data. The finding of the study is the author finding indicate a leak of clear methods for data pipeline approaches in response to user needs, and founding gaps in the literature regarding data management practice in industry.

On the other hand, DMBOK also provide Environmental Factor hexagon, show the relationship between people, process and technology and provides a key for reading the DMBOK context diagram. As Show in Figure 2.7:



Figure 2. 7. DAMA Environmental Factor Hexagon (DAMA International, 2017)

Figure 2.7. showing the Environmental factor hexagon that put goal & Principles on the center. Since these provides guidance for how people should execute activities effectively use the tools required for success data management (Henderson et al., 2017).

Data management encompasses the practical and technologies used to collect, store, and use data efficiently. In the logistic domain, this includes demand forecasting, route optimization, inventory control, and supplier performance tracking. Effective data management improve supply chains resilience and responsiveness.

Assessing data management maturity is essential for organizations like Company XYZ to understand where they stand and how to evolve. The DAMA-DMBOK framework defines a structured maturity model that helps organizations evaluate their capabilities across governance, data quality, and process consistency. This model supports decision-making by identifying maturity gaps and providing a roadmap for improvement (Hai, 2025). It consists of five progressive levels, from unstructured and reactive data management to highly optimized, predictive data governance. Each level represents a significant step toward enterprise-wide trust in data, efficiency, and risk

mitigation. The Figure 2.8 outlines the key characteristics of each maturity stage and what they imply for operational readiness (Henderson et al., 2017)

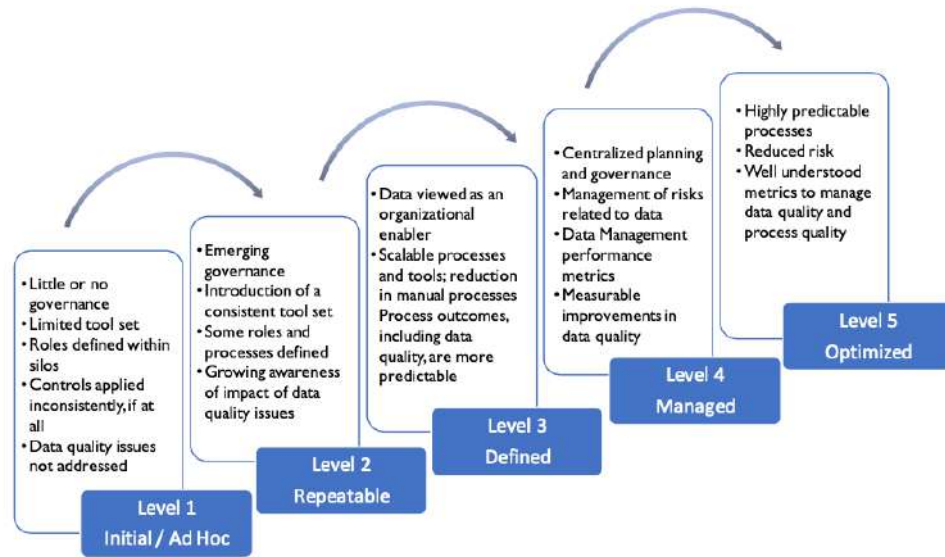


Figure 2. 8. Data Maturity Level DAMA-DMBOK(Henderson et al., 2017)

The Figure 2.8. illustrates the five maturity levels from DAMA-DMBOK. At Level 1, organizations operate in silos with minimal governance. Level 2 introduces basic tools and roles, marking the beginning of structured governance. At Level 3, data is recognized as a strategic enabler, and scalable processes emerge. Level 4 brings centralized planning, risk management, and measurable improvements in quality. Finally, Level 5 represents optimized maturity where processes are predictable, risks are low, and data metrics are deeply embedded into operations. Progression through these levels enables organizations to strengthen control, efficiency, and data-driven decision-making across the business.

#### 2.7.2. DCAM (The EDM Council's Data management Capability Management and Governance)

Beyond DMBOK, the literature identifies other framework and models that guide data management and governance. The EDM Council's Data Management Capability

assessment model (DCAM). DCAM first released in the financial industry, is another widely recognized framework that that capability maturity approach to data management. Another framework for comparison is DGI framework (Data Governance Institute) framework developed by Gwen Thomas. While DAMA-DMBOK and DCAM are comprehensive in term of content and maturity, the DGI framework offers a practical implementation roadmap for organization initiating their data governance journey.

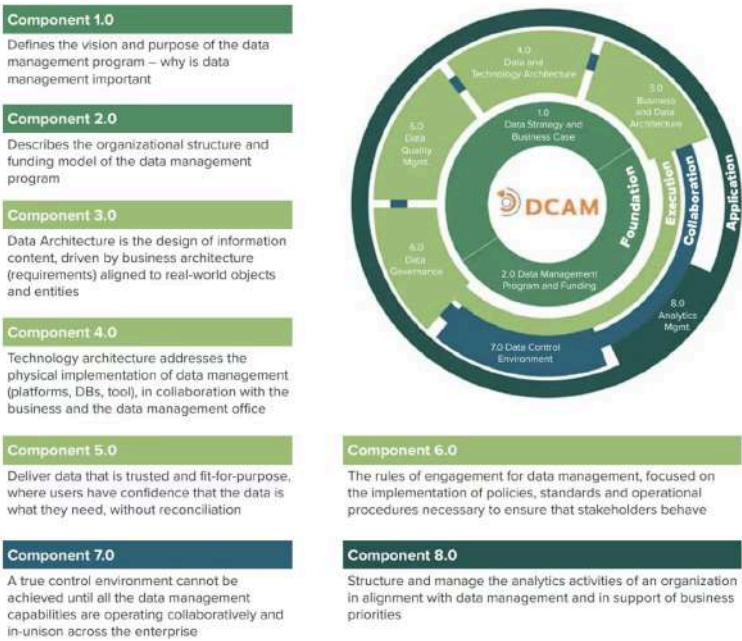


Figure 2. 9. DCAM v2.2 Framework (Pörtner et al., 2025)

The DCAM framework, as illustrated on Figure 2.9, presents a structured and integrated model of enterprise data management through eight interdependent components (Pörtner et al., 2025). It begins with defining the strategic vision and funding model (Components 1.0 and 2.0), followed by the alignment of business and technology architecture (Components 3.0 and 4.0) to support effective data design and system implementation. Execution is reinforced by ensuring data quality (Component 5.0) and enforcing governance through policies and standards (Component 6.0). These components are integrated within a collaborative control environment (Component

7.0), which ensures standardized implementation and consistent adoption across the organization. Furthermore, analytics management (Component 8.0) plays a critical role in overseeing analytical activities to ensure they are governed effectively and aligned with strategic business objectives. Collectively, these components establish a robust framework that positions data as a strategic asset—fostering consistency, trust, and value in data-driven decision-making processes.

### 2.7.3. DGI (The Data Governance institute)

The Data Governance Institute (DGI) framework offers a comprehensive methodology for implementing effective data governance practices. It provides a structured approach for defining policies, roles, and responsibilities to ensure data is managed with clarity, consistency, and accountability. The framework addresses key challenges such as data quality, compliance, and ownership by offering clear guidelines and industry best practices. Within the context of organizational data governance, the DGI framework is particularly valuable for formulating strategic data initiatives and enhancing data-driven decision-making processes.

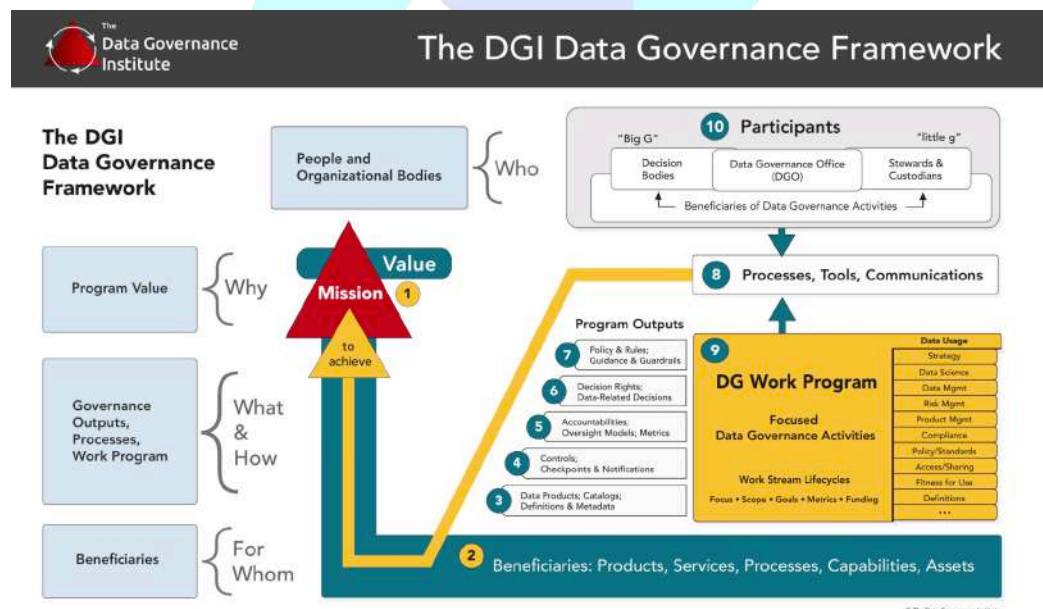


Figure 2. 10. The DGI Data Governance Framework (The Data Governance Institute, 2025)

As illustrated in Figure 2.10, the DGI Data Governance Framework provides a comprehensive model to help organizations design, implement, and sustain effective data governance programs by aligning strategic objectives with actionable components. The framework begins with a clearly defined mission and value proposition, ensuring that the governance initiatives directly support broader business goals (Bernardo et al., 2024). At the core of the framework is the Data Governance Work Program, which delivers essential outputs such as data policies, standards, decision rights, accountability structures, and control mechanisms. These outputs are executed through proactive and ongoing activities like data quality monitoring, lifecycle management, stewardship, and compliance enforcement.

The DGI framework highlights the critical role of organizational structures in effective data governance, including the establishment of data governance councils, a dedicated data governance office, and designated data stewards. These roles are essential for operationalizing governance policies and ensuring their execution across business units. In addition to role definitions, the framework integrates supporting tools, standardized processes, and structured communication channels to enable consistent governance practices throughout the organization. Collectively, these components foster transparency, accountability, and repeatability in data management and usage (Bližňák et al., 2024).

By explicitly linking governance initiative to beneficiaries such as products, services, business processes, capabilities, and assets. The DGI framework positions data governance as a strategic enabler rather than merely a compliance function. This alignment ensures that governance efforts contribute measurable value across the enterprise and support broader business objectives.

## **2.8. Optimizing Delivery Time, Cost, and Quality Trade-Offs**

In modern manufacturing and industrial engineering, managers must constantly balance competing objectives – typically delivery time, cost, and quality (often referred to as

the QCD or “iron triangle”). These trade-offs arise because reducing time or cost can degrade quality, and vice versa.

The trade-off between delivery time, price, and quality are crucial consideration in for a business strategy, practicality in the context of industrial trade engineering. These factors are often conflicting, and optimizing one may compromise the other. This response explores these trade-offs, drawing on insights from various paper to provide a comprehensive analysis.



Figure 2. 11. Balancing DCQ (Delivery, Cost, Quality)

Figure 2.11 illustrates the DCQ (Delivery, Cost, Quality) triangle in manufacturing, highlighting how businesses must strategically balance speed, affordability, and reliability achieving combinations such as fast and affordable, fast and reliable, or affordable and reliable while recognizing that excelling in all three simultaneously is rarely feasible.

### 2.8.1. Delivery Time in Manufacturing and Trade Engineering

Logistic decision in trade engineering industries system routinely involve conflicting objective of delivery time, cost, and quality. For example, supplier selection must balance price against delivery lead time and product quality, while routing and distribution must trade-off transport speed versus expense. While delivery time is a crucial factor, as it directly impacts customer satisfaction and market competitiveness. Research has shown that reducing delivery lead time can enhance customer satisfaction and loyalty (Zhang et al., 2024) (Tsai and Sugiarto, 2022). However, achieving shorter delivery time often requires additional resources, which may lead to increase operational cost. In cloud manufacturing environment, the scheduling of multi-user manufacturing tasks often fails to consider the impact of service supply on resource allocation, resulting in potential delay. A bi-objective multi-user, multi-task scheduling model has been proposed to minimize workload and maximize customer satisfaction by integrating factor: cost, time, and quality (Zhang et al., 2024). This approach enables organizations to optimize delivery performance without compromising service quality or increasing costs unnecessarily.

### 2.8.2. Cost Consideration in Manufacturing and Trade Engineering

Price/Cost is remaining critical factor in the manufacturing and trade engineering industry. Manufacturers often aim to minimize production costs while ensuring product quality and timely delivery. A study on multi-item fabrication-shipment decision models has shown that producers can achieve cost savings by adopting a postponement strategy, where the production of finished goods is delayed until customer orders are received (Lin et al., 2022). This approach reduces inventory holding costs and enables more adaptive production planning. However, from a logistics perspective, postponement may increase lead times, potentially affecting customer satisfaction, particularly for time-sensitive or mission-critical products. In such scenarios, customers may opt for faster alternatives, emphasizing the importance of logistics responsiveness alongside cost efficiency in maintaining competitive advantage.

### 2.8.3. Quality Assurance in Manufacture and Trade Engineering.

Quality is a non-negotiable factor in manufacturing and trade engineering, as it directly impacts customer satisfaction, brand reputation, and long-term loyalty. Research shown that quality can be enhance through reworking and screening processes in production planning (Lin et al., 2022). Their study on multi-item fabrication–shipment decision models incorporate quality assurance mechanisms—such as screening for defects and rework procedures—to ensure that only defect-free products are delivered. These practices not only support consistent quality standards but also contribute to minimizing returns and maintaining trust in the supply chain

### 2.8.4. Trade-off Analysis: Delivery Time, Price/Cost, and Quality

The trade-off between delivery time, price/cost, and quality is a complex problem that requires careful consideration of multiple factors. A study on time-cost-quality trade-off in material requirement planning (MRP) system has demonstrated that crashing MRP completion time can improve on-time delivery but may increase cost (Bagherpour et al., 2012). Similarly, a study on production project scheduling has shown that activity quality can be enhance by reworking, but this may lead to longer project duration (Ghasemi et al., 2023)

## **2.9. Mathematic Models and Artificial Intelligence Optimization for Time, Cost, and Quality Trade-off**

The trade-off between delivery time, price, and quality is a critical aspect of decision making in manufacturing and trade engineering industry. This exploration delves into the mathematic models use to optimize these factors.

### 2.9.1. Simplex Method

The simplex method is a widely use linear programming technique for optimizing time, cost, and delivery trade-off. It is particularly effective for solving linear optimization problem with multiple constraints. However, its application in real world scenarios is limited by its inability to handle non linier relationship and uncertainty.

The Simplex Method is a widely used mathematical algorithm in logistics operations to optimize cost, improve delivery time, and maintain product quality. As a linear programming tool, it is particularly useful in solving transportation and distribution problems, where logistics managers aim to allocate resources or routes in the most efficient way. The method works iteratively to find the optimal solution, making it reliable for complex but structured logistics problems (Prokudin et al., 2022) (Ndubuisi, 2021).

In practical applications, the Simplex Method has shown strong performance in minimizing costs in courier distribution, cold chain logistics, and perishable goods transportation, while still ensuring timely delivery and product quality (Xu et al., 2020). It has also been combined with metaheuristic techniques such as Ant Colony Optimization (ACO) and the Football Game Algorithm (FGA) to handle more complex routing problems like the Capacitated Vehicle Routing Problem (CVRP), showing its flexibility in integrated systems (Calabrò et al., 2020) (Alif et al., 2022).

Table 2. 7. Strengths and Weakness of Simplex Method

| Strength                                                                                       | Reference                                 |
|------------------------------------------------------------------------------------------------|-------------------------------------------|
| Efficiency: It solves large-scale linear problems relatively quickly.                          | (Ndubuisi, 2021; Prokudin et al., 2022)   |
| Accuracy: It guarantees an optimal solution for well-defined problems.                         | (Anisimov et al., 2021; Xu et al., 2020)  |
| Adaptability: It can be combined with other methods to extend its use in real-world logistics. | (Alif et al., 2022; Calabrò et al., 2020) |

| Weakness                                                                                                                                                             | Reference                                      |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------|
| Linearity Assumption: It assumes linearity, meaning it cannot fully model real-world conditions like fluctuating demand, nonlinear costs, or unexpected disruptions. | (Anisimov et al., 2021; Prokudin et al., 2022) |
| Scalability: For very large or dynamic networks, it may become computationally heavy and less practical                                                              | (Ndubuisi, 2021; Xu et al., 2020)              |

Table 2.7 The table summarizes the key strengths and weaknesses of the Simplex Method in logistics, highlighting its optimization capabilities as well as its limitations in handling real-world complexity.

2.9.2. Fuzzy Logic Model

The integration of fuzzy logic into mathematic model for logistic operations has emerged as a powerful approach to address the inherent uncertainties and imprecision in decision making processes. This is particularly relevant in engineering trade industries, where the trade-offs between delivery time, cost, and quality are critical. Fuzzy logic provides a robust framework to handle vague and ambiguous data, making it an ideal tool for modeling complex logistic operations.

Fuzzy logic is mathematic approach to deal with uncertainty and imprecision, making it highly suitable for real-word logistic problems where data is often uncertain or vague. In logistic, fuzzy logic has been applied to various problems, including vehicle routing, inventory management, and supply chain optimizations. The ability of fuzzy logic to handle linguistic variables and approximate reasoning makes it a valuable tool for modeling complex systems (Alaoui et al., 2023; Radovanović, 2024)

A mathematic model for decision-making in logistics has been developed using fuzzy set theory. This model minimized production and technological cost while considering the rationally of routes and the choice of the best option.

Table 2. 8. Strength and Weaknesses of Fuzzy Logic in Logistic Trade Industries

| Aspect                              | Description                                                                                                                     | Reference                                      |
|-------------------------------------|---------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------|
| <b>Strength</b>                     |                                                                                                                                 |                                                |
| Handling Uncertainty & Nonlinearity | Effectively manages vague or incomplete data, making it ideal for real-world logistics challenges with unpredictable variables. | (Haghighi and Mousavi, 2022)                   |
| Multi-Objective Optimization        | Enables balancing of competing goals such as time, cost, and quality through systematic trade-off analysis.                     | (Liu et al., 2023)(Banihashemi et al., 2021)   |
| Flexibility & Adaptability          | Can be applied across various logistics problems and data structures due to its high adaptability.                              | (Chauhan et al., 2023) (Sapan Kumar Das, 2022) |
| Enhanced Decision-Making            | Supports complex decision-making by incorporating multiple criteria and stakeholder preferences.                                | (Banihashemi et al., 2021)                     |
| Complexity & Computational Demand   | Solving large-scale logistics problems can require significant computing resources,                                             | (Chauhan et al., 2023) (Sapan Kumar Das, 2022) |

| Aspect                       | Description                                                                                                             | Reference                                      |
|------------------------------|-------------------------------------------------------------------------------------------------------------------------|------------------------------------------------|
| Strength                     |                                                                                                                         |                                                |
|                              | affecting real-time application.                                                                                        |                                                |
| Lack of Standardization      | Multiple modeling approaches make it difficult to compare and select the best model consistently.                       | (Haghighi and Mousavi, 2022)                   |
| Reliance on Expert Knowledge | Requires expert input to design membership functions and fuzzy rules, which may not always be available.                | (Banihashemi et al., 2021), (Liu et al., 2023) |
| Limited Interpretability     | Models can be complex and hard to interpret for non-expert users, reducing practical usability in logistics operations. | (Sapan Kumar Das, 2022)                        |

The table 2.8. provides a summary of the strengths and weaknesses of fuzzy logic models in logistics operations, highlighting their ability to handle uncertainty and multi-objective decisions, alongside challenges related to complexity, standardization, and expert dependency.

2.9.3. Artificial Intelligence Optimization

The integration of Artificial intelligence (AI) in supply chain optimization has emerged as a transformative force in the engineering trade industry. By leveraging AI technology, business can enhance efficiency, reduce operational cost, and improve quality of logistics operations.

AI technology, including machine learning (ML), predictive analytics, and real time data processing, have revolutionized supply chain management. these technologies enable business to forecast demand more accurately. Optimize inventory levels, and streamline logistic operations (Hasan et al., 2024), (Zhang, 2024).

Study by Nweje also highlight the AI driven predictive analytics enhance demand forecasting accuracy by analyzing historical data, market trend, and external factor such as economic shifts and weather conditions. The finding, its reduce stockouts and excess inventory, improving operational efficiency and customer satisfaction (Nweje and Taiwo, 2025). In other hand, Study by Pasupuleti also find that AI able to optimize inventory levels by predicting demand variability and automating replenishment processes. For instance, machine learning algorithms can identify at risk shipments and reduce overstock and stockout by up to 10% (Pasupuleti et al., 2024). Ai also able to improve route planning and transportation management by dynamically scheduling vehicles and minimizing transportation cost (Li et al., 2021). Another study by Attah and Ried have similar finding, AI enables real time monitoring of supply chain operation, allowing businesses to respond dynamically to disruptions and optimize resource allocation (Attah et al., 2024) (Riad et al., 2024).

To successfully implement AI in supply chain and logistics operations, several best practices must be considered. According to a study by Fernando, businesses should first assess their organizational readiness, which includes evaluating data quality, the skill level of human resources, and the level of management support (Fernando et al., 2024). Since AI systems rely heavily on high-quality data to generate accurate insights, Pasupuleti emphasizes the importance of investing in robust data collection and analytics capabilities to maximize the benefits of AI (Pasupuleti et al., 2024) (Nweje and Taiwo, 2025). Another critical factor is the integration of AI with existing systems; as highlighted by Adenekan and Chodhuri, AI solutions must be seamlessly integrated with ERP systems and supply chain management tools to ensure smooth data exchange and full end-to-end visibility (Adenekan et al., 2024) (Choudhuri, 2024). Furthermore, Ejjami underline the need for continuous monitoring and updating of AI models to

address potential biases, maintain transparency, and adapt to evolving market conditions (Ejjami and Boussalham, 2024).

## **2.10. Previous Studies**

### **2.10.1. Summary Of Framework**

Indonesia's logistic sector faces significant challenges, as reflected in its drop to 61<sup>rd</sup> place in the 2023 Logistic Performance Index (LPI) a 15 rank decline from 46<sup>th</sup> in 2018 (World Bank, 2023). This underperformance stems from high logistics cost, which account for 24% of Indonesia's GDP. For Company XYZ Indonesia, logistics expenses represent 14% of operational costs, far exceeding the 8-10% average of its branches in Singapore, Thailand, and Malaysia base on internal business report for years 2024. Such inefficiencies highlight the urgent need for data driven strategies to optimize costs and delivery time through sophisticated data analytics and procedures to extract useful insight from the data (Jin and Kim, 2018) (Hatamlah et al., 2023).

The CRISP-DM framework emerges as a foundational methodology for structuring data analytics projects. Its six phase approach spanning business understanding, data understanding, data preparation, modelling, evaluation, and development has proven effective in engineering sector, as demonstrated by (Brzozowska et al., 2023) in production optimization and (Massmann et al., 2020) in product planning. CRISP-DM framework adopted as the primary analytic methodology to guide the data driven problem solving process. This framework is widely recognized for its effectiveness in analytic and predictive modeling across industries, including logistics and supply chain management. However, to ensure that the data used within the CRISP-DM cycle is governed consistent, and high quality, this study integrates the DAMA-DMBOK (Data Management Body of Knowledge) framework. DAMA-DMBOK serves as a complementary structure by providing detailed practices and principle for managing and governing data across its lifecycle. It encompasses critical domains such as Data Governance, Data Quality, Master Data Management, Data Architecture, and Data Integration area that CRISP-DM does not explicitly cover but are essential for effective analytics in complex environment like logistics operations.

While ODM-BDA offers high accuracy and real-time analytics capabilities for large-scale environments, its implementation complexity, reliance on cloud infrastructure, and need for specialized talent present significant barriers for mid-sized companies (Niu et al., 2021). Furthermore, its limited theoretical maturity and high privacy risk concerns make it less ideal for structured logistics optimization projects. In contrast, CRISP-DM provides a more practical, proven approach that integrates well with existing tools (Power BI, PowerApps) and governance frameworks DAMA-DMBOK ensuring a better fit for structured analytics on cost efficiency and delivery time improvement initiatives.

The integration of CRISP-DM with DAMA-DMBOK support the governance of operational, logistical and business critical data across its full lifecycle. As outline by Li (Li et al., 2024), DAMA-DMBOK define data governance as “the exercise of authority, control, and shared decision making over the management of data assets.” Establishing policies, ownership roles, ad quality standards. This aligns well with the needs of industrial and trading firms, such as company XYZ, where inconsistent data and unclear ownership have led to report delays and inefficiencies in logistics operations (Sigi, 2024). By implementing the DAMA-DMBOK framework alongside CRISP-DM, the organization can formalize roles. For instance, data stewards. And asses data maturity across the ten DAMA domains, and ensure that key logistics data such a shipment status, inventory levels, and supplier performance is accurate, timely, and usable for predictive modeling.

Although other frameworks like DCAM and DGI offer value in enterprise data governance, they were not selected for this study due to certain limitations in relation to the research objectives.

The DCAM framework, developed by the EDM Council, provides a capability-based assessment model primarily focused on strategic maturity evaluation and regulatory compliance. While DCAM includes components for governance, data quality, and analytics alignment, it is particularly suited to financial institutions and regulatory-driven environments (Pörtner et al., 2025). In the context of this study, DCAM’s focus

on strategic vision, control environments, and enterprise-wide analytics governance is too high-level to address the operational challenges faced in logistics execution and process optimization. As reported by Sigi (Sigi, 2024), firms in the trade and industrial sector struggle with fragmented systems and inconsistent data standards—issues more directly addressed by DAMA-DMBOK’s operational domains, such as data integration and master data management.

The DGI Framework offers a practical and structured roadmap for organizations beginning their data governance journey. It emphasizes roles, responsibilities, policies, and decision rights (Bernardo et al., 2024), making it an excellent model for governance setup. However, the DGI model remains conceptual and policy-driven, without detailed guidance on data quality techniques, architecture implementation, or stewardship maturity. In complex logistics operations, where analytics depend on consistent and integrated data sources, the DGI framework lacks the technical granularity necessary to support CRISP-DM implementation. Additionally, DGI’s value is strongest during the initiation phase of governance, while this study requires a model that supports ongoing data operations and process monitoring.

Table 2. 9. Comparison and Justification for selecting DAMA-DMBOK over DCAM and DGI frameworks

| Criteria        | DAMA-DMBOK                                                     | DCAM (EDM Council)                                                             | DGI Framework                                                    |
|-----------------|----------------------------------------------------------------|--------------------------------------------------------------------------------|------------------------------------------------------------------|
| Focus Area      | Comprehensive data management and governance across 11 domains | Capability assessment and maturity benchmarking for enterprise data management | High-level data governance policies, roles, and responsibilities |
|                 |                                                                |                                                                                |                                                                  |
| Level of Detail | High: Offers operational-level                                 | Medium: Focused on strategic capability                                        | Low–Medium: Policy-oriented,                                     |

| Criteria                    | DAMA-DMBOK                                                                                       | DCAM (EDM Council)                                                                    | DGI Framework                                                                |
|-----------------------------|--------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------|------------------------------------------------------------------------------|
|                             | practices (e.g., data quality, architecture, integration)                                        | building rather than operational application                                          | limited technical or operational guidance                                    |
| Best Fit With CRISP-DM      | ✓ Complements each CRISP-DM phase with actionable data practices                                 | ✗ Lacks direct operational alignment with CRISP-DM analytics process                  | ✗ Focuses more on roles and governance structure than analytics lifecycle    |
| Use in Logistics Operations | ✓ Proven effective in addressing logistics data challenges (e.g., integration, quality, lineage) | ✗ Primarily used in financial services and risk-based environments                    | ✗ Best suited for initiating governance programs, not logistics optimization |
| Maturity Assessment Support | ✓ Provides structured maturity models across all data management domains                         | ✓ Strong in capability assessment, but limited operational improvement support        | ✗ No formalized maturity model                                               |
| Ease of Implementation      | Medium: Requires coordination across domains but has broad applicability                         | Low: Often requires external consultants and is resource-intensive                    | High: Easy to initiate but lacks operational follow-through                  |
| Justification for Selection | Best suited for operationalizing governed data within                                            | Not aligned with the logistics focus and lacks implementation tools for analytics use | More suitable for early-stage governance setup,                              |

| Criteria | DAMA-DMBOK                                        | DCAM (EDM Council) | DGI Framework                      |
|----------|---------------------------------------------------|--------------------|------------------------------------|
|          | analytics processes like<br>CRISP-DM in logistics |                    | not in-depth<br>analytics projects |

Base on the comparison on Table 2.9, DAMA-DMBOK is selected as the most appropriate framework to complement CRISP-DM in this study. Unlike DCAM, which focuses on high-level capability assessments, and DGI, which centers on governance roles and policies, DAMA-DMBOK offers both the comprehensive scope and operational depth required to manage data effectively in logistics-driven analytics environments. Its strong alignment with data preparation, integration, and quality assurance activities makes it a natural fit to support each phase of the CRISP-DM process and drive actionable improvements in cost, delivery time, and product quality.

With the implementation of a structured data governance framework—particularly through the DAMA-DMBOK approach—the organization has established the critical foundation for ensuring data consistency, ownership, integration, and accessibility across its logistics and manufacturing operations. This foundation is not the final objective but rather a prerequisite for enabling higher-value initiatives. Once data is governed effectively, the organization can progress to the next strategic phase: optimizing the trade-offs between delivery time, logistics cost, and product quality. These three elements represent a constant balancing act in industrial and trade engineering environments, and managing them efficiently is crucial to maintaining customer satisfaction, operational efficiency, and long-term competitiveness.

Data governance has emerged as a critical enabler for ensuring high-quality, accessible, and reliable data in logistics and supply chain operations. In the context of this research, the implementation of data governance focuses specifically on four key domains from the DAMA-DMBOK framework: Data Quality, Data Architecture, Reference and Master Data Management, and Data Storage and Operations. These domains were selected based on their direct relevance and practicality in addressing operational inefficiencies, especially those related to logistics cost and delivery performance.

(Božić et al., 2024) emphasize the significant influence of product master data quality on logistics performance. Their study, conducted within industrial supply chain environments, highlights how inconsistencies in product data such as incorrect dimensions, weights, or identification codes can lead to process disruptions and increased handling time. Conversely, when master data quality is assured, logistics processes become more efficient and accurate, particularly in order fulfilments and warehouse operations. This reinforces the importance of governing both data quality and reference/master data in a unified structure to support logistics performance.

Further supporting this view, (Nair, 2025) discusses the strategic role of Master Data Management (MDM) in supply chain operations. His study found that organizations with structured MDM practices achieved notable improvements in operational metrics, including faster processing times and enhanced inventory accuracy. The author also reports that clean, governed master data reduced supplier onboarding times and improved collaboration across procurement and logistics teams. These findings affirm that master data governance, when combined with quality assurance mechanisms, enables more agile and data-driven logistics management.

In parallel, the domain of data architecture is identified as a key structural element in modern supply chains. (Xiros et al., 2025) propose a comprehensive data architecture framework for supply chain digital twins, demonstrating how an integrated architecture facilitates seamless data flow between systems. The study illustrates that an effective data architecture, supported by standardized storage and interoperable platforms, enables advanced analytics and real-time decision-making. This insight is particularly relevant for logistics operations, where timely data access and system alignment are vital for shipment tracking, cost monitoring, and vendor performance evaluation.

Complementing the architectural aspect, (Barzizza et al., 2023) underscore the necessity of centralized data storage and operations in the era of Supply Chain 4.0. Their literature review reveals that companies adopting big data infrastructure and centralized storage solutions experience improved data availability, which in turn enhances analytics capabilities and decision-making accuracy. Without proper data

storage governance, supply chain organizations face challenges in consolidating fragmented data sources, leading to delays and limited operational visibility.

Collectively, these studies affirm that a focused implementation of selected DAMA-DMBOK domains particularly data quality, data architecture, reference and master data, and data storage and operations can establish a robust data governance foundation in logistics environments. This targeted approach is not only practical within the scope of logistics data management but also aligned with the broader goals of operational efficiency, cost optimization, and delivery reliability.

Table 2. 10. Table summaries of Domains used from DAMA-DMBOK Framework

| DAMA-DMBOK Domain         | Key Insights                                                                                                                                                  | Supporting Literature  | Logistics Implication                                                                                   |
|---------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|---------------------------------------------------------------------------------------------------------|
| Data Quality              | Inconsistencies in product data (e.g., dimensions, weights, IDs) disrupt logistics workflows and increase handling time. High-quality data enhances accuracy. | Božić et al. (2024)    | Improves order fulfilments and reduces processing errors.                                               |
| Reference & Master Data   | Structured MDM leads to faster processing, improved inventory accuracy, and efficient supplier onboarding.                                                    | Nair (2025)            | Supports collaboration and agility in procurement and logistics functions.                              |
| Data Architecture         | Integrated data architecture supports seamless system connectivity and enables real-time analytics through digital twins.                                     | Xiros et al. (2025)    | Enables advanced monitoring (e.g., cost tracking, vendor performance) and decision-making in logistics. |
| Data Storage & Operations | Centralized storage improves data availability, supporting                                                                                                    | Barzizza et al. (2023) | Enhances decision-making accuracy and                                                                   |

| <b>DAMA-<br/>DMBOK<br/>Domain</b> | <b>Key Insights</b>                                                                        | <b>Supporting<br/>Literature</b> | <b>Logistics Implication</b>                                          |
|-----------------------------------|--------------------------------------------------------------------------------------------|----------------------------------|-----------------------------------------------------------------------|
|                                   | analytics and operational<br>visibility; fragmentation leads<br>to delays and blind spots. |                                  | consolidates logistics<br>data sources for end-to-<br>end visibility. |

Table 2.10 presents a synthesized view of four DAMA-DMBOK domains, Data Quality, Reference and Master Data Management, Data Architecture, and Data Storage and Operations that were strategically selected for implementation in logistics data governance within this study. Each domain demonstrating its practical impact on logistics performance. The insights emphasize how improved data quality reduces process errors, how structured master data enhances operational agility, how robust architecture enables system integration and analytics, and how centralized storage supports visibility and timely decision-making. Together, these domains form a cohesive foundation for enabling data-driven improvements in logistics cost management and delivery efficiency.

While the DAMA-DMBOK framework encompasses a comprehensive range of data management domains, not all of them are equally relevant or necessary in every organizational context. In logistics optimization, where the primary focus is on reducing cost and improving delivery performance, a fit-for-purpose governance approach is often adopted. This means selecting only those domains that directly support the business objectives at hand. The remaining domains were excluded for the following reasons.

Data Modelling and Design is not addressed as a separate governance activity because this thesis applies the CRISP-DM framework, which inherently includes modelling as a core step. Thus, a dedicated governance structure for modelling and design is unnecessary. Data Security is managed by enterprise-level IT teams, and given that the logistics data used in this study does not involve personal or sensitive information, security-specific governance is considered out of scope. Data Integration is treated as

part of the Data Architecture domain, aligning integration efforts with system design and interoperability without duplicating governance functions.

Document and Content Management is excluded because logistics operations primarily rely on structured transactional data such as order numbers, shipment records, and delivery timestamps. The role of unstructured data (e.g., scanned documents or emails) is minimal and not central to logistics optimization, making governance in this domain unnecessary. Similarly, Data Warehousing and Business Intelligence are not emphasized since the CRISP-DM framework already supports operational analytics through tools like Power BI, eliminating the need for centralized data warehousing. Lastly, Metadata Management is embedded within Master Data and Data Quality activities in this thesis, where metadata standards and documentation practices are maintained without formalizing a separate governance domain.

In summary, the exclusion of these domains reflects a strategic decision to prioritize only those governance areas that contribute directly to logistics performance improvement. This approach ensures governance efforts remain practical, measurable, and aligned with operational needs, consistent with context-driven governance principles proposed in recent literature.

#### 2.10.2. Choice of Logistic Improvement Process

As depicted in Figure 2.11, the DCQ (Delivery, Cost, Quality) triangle reflects the inherent tension among these goals, where improving one often comes at the expense of another. Informed by high-quality and well-governed data, decision-makers can now more accurately assess and manage these trade-offs. For instance, reducing delivery time is vital for meeting customer expectations and enhancing market responsiveness, as supported by studies that show faster fulfillment improves loyalty and satisfaction (Zhang et al., 2024) (Tsai and Sugiarto, 2022). However, rapid delivery must be balanced against the need to minimize logistics-related costs, including transportation, warehousing, and inventory handling areas where strategies like postponement or dynamic routing can offer cost savings without sacrificing efficiency (Lin et al., 2022).

At the same time, product quality must remain non-negotiable. In competitive trade environments, the delivery of defect-free, reliable goods is not just a differentiator, it is a baseline expectation. While practices such as rework and screening can enhance quality (Ghasemi et al., 2023), they must be integrated into workflows in a way that does not undermine lead times or inflate logistics costs.

Therefore, the transition from data governance to operational optimization is both logical and necessary. Governed data becomes the enabler for intelligent decision-making across logistics functions. Allowing organizations to prioritize improvements that reduce delivery delays, control cost exposure in the supply chain, and deliver consistently high-quality products. In doing so, the organization not only addresses the trade-offs but turns them into opportunities for continuous improvement and competitive advantage.

To ensure analytical rigor in the optimization process, the use of mathematical models is considered. Techniques such as the Simplex Method, Fuzzy Logic, and Artificial Intelligence are recognized for their capabilities in addressing trade-offs among delivery time, cost, and quality. However, given the specific problem and the contextual constraints at Company XYZ, a simulation-based scenario was selected for this study. This decision is primarily driven by the current stage of data governance implementation, during which the available data is still undergoing quality improvements. As a result, the quantity of high-quality, reliable data remains insufficient to support the application of more complex mathematical models at this time.

Nevertheless, understanding the potential of these mathematical models remains valuable, particularly for informing future optimization initiatives as data maturity improves. The following discussion reviews the capabilities and limitations of selected models—Simplex Method, Fuzzy Logic, Artificial Intelligence, and Simulation Base Scenario—and outlines the key considerations that led to their exclusion from this phase of the study.

The Simplex Method is a proven linear programming technique known for its efficiency in solving structured optimization problems involving multiple constraints (Prokudin et al., 2022) (Ndubuisi, 2021). It has demonstrated strong applicability in logistics areas such as courier distribution, cold chain management, and resource allocation—delivering cost minimization and delivery improvement while maintaining product quality (Xu et al., 2020). Additionally, it is adaptable, as it can be extended with other algorithms (e.g., Ant Colony Optimization, Football Game Algorithm) for routing or capacity challenges (Calabrò et al., 2020) (Alif et al., 2022).

While Fuzzy Logic offers strengths in handling uncertainty and multi-objective optimization—particularly valuable in scenarios involving vague, nonlinear, or incomplete data (Haghighi and Mousavi, 2022) (Banihashemi et al., 2021) requires substantial computational power and expert-driven configuration of membership functions and fuzzy rules. In Company XYZ's context, these requirements present a significant barrier due to the current absence of specialized personnel and the added complexity of model validation and interpretability (Satya Kumar Das, 2022) (Chauhan et al., 2023).

Moreover, AI-based models such as machine learning or neural networks were excluded from this study due to internal policy at Company XYZ. Specifically, the use of AI requires prior approval from the company’s global headquarters, which is time-consuming and not feasible within the scope of this research. Additionally, AI model deployment would require technical expertise that is currently not available in the Indonesian branch. However, these advanced models may be suitable for future studies once the regulatory and organizational capacity permits.

Table 2. 11. Optimization Methods Features Checklist Table

| Feature                           | Simulation |       |    |           |
|-----------------------------------|------------|-------|----|-----------|
|                                   | Simplex    | Fuzzy | AI | Base      |
|                                   |            |       |    | Scenarios |
| Efficient for structured problems | ✓          | ✗     | ✗  | ✗         |

| Feature                                     | Simplex | Fuzzy | AI | Simulation        |
|---------------------------------------------|---------|-------|----|-------------------|
|                                             |         |       |    | Base<br>Scenarios |
| Proven in logistics use cases               | ✓       | X     | X  | ✓                 |
| Supports cost and delivery optimization     | ✓       | ✓     | ✓  | ✓                 |
| Transparent and easy to explain             | ✓       | X     | X  | ✓                 |
| Handles vague/incomplete data               | X       | ✓     | ✓  | X                 |
| Balances multiple objectives                | X       | ✓     | ✓  | X                 |
| Suitable for uncertain scenarios            | X       | ✓     | ✓  | X                 |
| Learns from data over time                  | X       | X     | ✓  | X                 |
| Real-time/dynamic optimization              | X       | X     | ✓  | X                 |
| Forecasting and automation                  | X       | X     | ✓  | X                 |
| Easy to visualize results                   | X       | X     | X  | ✓                 |
| Supports what-if/scenario testing           | X       | X     | X  | ✓                 |
| Captures process interactions               | X       | X     | X  | ✓                 |
| Assumes linearity and certainty             | ✓       | X     | X  | X                 |
| Less effective in nonlinear/uncertain cases | ✓       | X     | X  | X                 |
| Requires expert knowledge                   | X       | ✓     | ✓  | X                 |
| High computational demand                   | X       | ✓     | ✓  | X                 |
| Complex model validation                    | X       | ✓     | ✓  | X                 |
| High cost and complexity                    | X       | X     | ✓  | X                 |
| Needs skilled personnel / HQ approval       | X       | X     | ✓  | X                 |
| Not real-time                               | X       | X     | X  | ✓                 |
| Dependent on scenario assumptions           | X       | X     | X  | ✓                 |
| Limited generalization                      | X       | X     | X  | ✓                 |

Table 2.11 provides a comparative checklist of four optimization approaches: Simplex Method, Fuzzy Logic, AI-Based Models, and Simulation-Based Optimization, evaluated based on their strengths, weaknesses, and feasibility in the context of Company XYZ. While all models offer valuable capabilities for balancing logistics cost, delivery time, and quality, simulation-based optimization is identified as the most suitable approach due to its practicality and alignment with the current stage of data governance and data availability.

#### 2.10.3. Visualization Method

For designing Business Intelligent tools using Microsoft Power BI, this thesis also continue to utilize CRISP-DM framework, combined with business intelligence architecture framework on the visualization phase originally developed by (Ranjan, 2009). The Framework was successfully applied by (Kongthanasuwan et al., 2023) for developing the business intelligence for automatic industries in Thailand. The study by (M. A. Khan et al., 2020) also finding that the business intelligence architecture ensures generate fast and accurate reports.

Research from previous study has shown that Business Intelligence (BI) system like Microsoft PowerApps have a significant impact on improving strategic decision-making in various industries (Abu-AlSondos, 2023). This system helps by offering insights through tools like data visualization, BI management, and ensuring data quality, which leads to better decision-making. Additionally, Business Intelligence tools are valued for their ability to integrate data, analyze it, and provide real-time update which support the quick and flexible decision-making needed in today's competitive environment according to study by (Gonçalves et al., 2023) (Jin and Kim, 2018), (Hatamlah et al., 2023).

In the context of logistics performance improvement, particularly delivery time and cost monitoring visualization play a crucial role in enabling real-time decision-making. The integration of Microsoft Power Apps and Power BI into the development cycle

empowers organizations to deploy interactive dashboards that respond to user roles and business needs. To ensure effective and agile development of these tools, this study adopts a hybrid approach, combining the Agile Software Development Life Cycle (SDLC) with the CRISP-DM framework.

The Agile methodology is selected due to its compatibility with low-code platforms like Power Apps and its iterative nature, which facilitates early delivery of working solutions, user collaboration, and continuous improvement (Mishra and Alzoubi, 2023). Agile allows logistics teams to quickly build and refine visualization tools such as dashboards for monitoring delivery lead time and cost per shipment by involving stakeholders (e.g., supply chain managers, operations teams) in every sprint. This supports incremental feature deployment, such as role-based access, automated KPI alerts, or layout refinement based on user feedback.

Furthermore, this approach is enhanced through the structure of the CRISP-DM framework, which guides the entire data-driven development process—from understanding business needs and data preparation to modelling and deployment. As seen in the framework (Figure 3.1), the visualization component aligns with CRISP-DM phases such as "Business Understanding" (defining monitoring objectives and cost drivers), "Data Understanding" (identifying user roles and data fields), and "Deployment" (centralizing dashboards and improving over time). CRISP-DM ensures that the visualization tools are not only technically sound but also aligned with broader strategic goals.

This integration enables agile teams to translate iterative requirements into data models and BI components efficiently. For instance, logistics dashboards developed through this method have demonstrated improvements in delivery time cycle tracking and cost transparency.

Table 2. 12. SDLC Model Comparison for Project in Logistic

| <b>SDLC Method</b> | <b>Development Speed</b> | <b>Stakeholder Collaboration</b> | <b>Automation Integration</b> | <b>Suitability for Power Platform</b> |
|--------------------|--------------------------|----------------------------------|-------------------------------|---------------------------------------|
| Waterfall          | Slow                     | Low                              | Rigid                         | Poor                                  |
| Iterative          | Medium                   | Moderate                         | Flexible per iteration        | Good                                  |
| Agile              | Fast                     | High                             | High (supports sprints)       | Excellent                             |

Table 2.12 shows a comparison of four SDLC methods: Waterfall, Iterative, Agile, in the context of logistics monitoring using Microsoft Power Apps and Power Automate. Agile offers the best balance of development speed, user collaboration, and flexible automation integration, making it the most suitable for low-code, data-driven projects. While iterative provides moderate flexibility, and Waterfall is the least adaptable due to its rigid structure.

The visualization layer in this framework is best served through an Agile SDLC approach, where role-based dashboards are developed and refined in cycles, using tools such as Power Apps and Power BI. Coupled with CRISP-DM, this method ensures the dashboard evolves based on business understanding, user interaction, and validated data modelling. This structured yet flexible approach supports the continuous monitoring and improvement cycle shown in the deployment phase of the framework.

While the platform and framework support both cost and delivery performance monitoring, this research focuses primarily on delivery time monitoring through PowerApps. The visualization of cost drivers is planned as a continuation project beyond the current implementation timeline.