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Optimizing Supplier Delivery Reliability in Project-Driven Supply Chains through AI-Supported Value Stream Mapping

A Data-Driven Framework for Enhancing Coordination and Predictive Control

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ABSTRACT:

This thesis explores how artificial intelligence (AI) can be integrated into project-driven supply chains (PDSCs) to improve supplier delivery reliability. The research focuses on a real Engineer-to-Order (ETO) project in the energy sector, where delivery delays and coordination gaps exposed structural weaknesses in procurement and logistics. A simplified Value Stream Mapping (VSM) approach was used to analyze the delivery flow and identify where reliability breaks down.

Three AI models were introduced to support earlier decision-making. LightGBM was positioned to flag delay risks after supplier confirmation. A fuzzy inference system (FIS) was used to assess shipment readiness from incomplete signals. Clustering was applied for post-delivery supplier segmentation. One model—FIS—was simulated using real shipment data and confirmed to match high-frequency coordination failures. The others were validated through interviews and mapped to case data. Applied studies showed that these models improve forecasting reliability and streamline logistics decision-making in environments similar to the case context.

The redesign does not propose automation. It introduces predictive checkpoints where human judgment is weakest. Procurement and logistics staff confirmed the realism of the approach and expressed interest in piloting readiness scoring and segmentation tools. A phased roll-out strategy was proposed, starting with Excel and PowerBI overlays before deeper integration. The findings show that interpretable AI can improve operational clarity and strengthen Lean coordination—without disrupting existing workflows. This creates a foundation for smarter, more reliable project execution.

Keywords: Project-Driven Supply Chains, Supplier Coordination, Value Stream Mapping, Artificial Intelligence, Delivery Reliability, LightGBM, Fuzzy Inference System, Clustering.

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List of Abbreviations

VSM	Value Stream Mapping
AI	Artificial Intelligence
PDSC	Project-Driven Supply Chain
SSB	Smart Strategy Board
BMC	Business Model Canvas
EPC	Engineering, Procurement, and Construction
SAP	Systems, Applications, and Products in Data Processing
SCRM	Supply Chain Risk Management
TPS	Toyota Production System
RFQ	Request for Quotation
PO	Purchase Order
XF	Field Fault
QE	Quality Error
QV	Quality Verification
ERP	Enterprise Resource Planning
ETO	Engineer-to-Order
NDA	Non-Disclosure Agreement
ANN	Artificial Neural Network
FIS	Fuzzy Inference System

ML	Machine Learning
KPI	Key Performance Indicator
XGBoost	Extreme Gradient Boosting
CatBoost	Categorical Boosting
GNN	Graph Neural Network
RL	Reinforcement Learning
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
PowerBI	Power Business Intelligence
PLT	Procurement Lead Time
DR	Delivery Reliability
VAT	Value-Added Time
MW	Megawatt
LightGBM	Light Gradient Boosting Machine
GR	Goods Receipt
Incoterm	International Commercial Term
FCA	Free Carrier
DAP	Delivered at Place
DDP	Delivered Duty Paid
ESG	Environmental, Social, and Governance
AHP	Analytic Hierarchy Process
RDD	Raw Delivery Deviation
DWCR	Delivery Window Compliance Rate
DV	Deviation Variability
ETA	Estimated Time of Arrival
AIS	Automatic Identification System

Chapter 1

Introduction

This chapter opens the thesis by introducing the supplier coordination challenges faced in Project-Driven Supply Chains (PDSCs). It defines the research problem and presents the research question on improving delivery reliability through Artificial Intelligence (AI) integration. It also outlines the study's objectives, scope, and structure. Together, these elements frame the motivation and direction for the chapters that follow.

1.1 Background

Supply chains today do more than manage costs. In complex project environments, they have become critical enablers of coordination and control (Simchi-Levi et al., 2011). In stable industries, deliveries benefit from predictable demand. Inventory buffers and planning cycles further stabilize the flow.

These conditions do not apply to PDSCs, which are built around temporary, milestone-based projects such as energy or infrastructure initiatives (Basu, 2011). Orders are engineered to order, sourced once, and expected to arrive just in time. The absence of inventory buffers makes delays especially costly. Chapter 2 expands on the structural and operational differences that define these supply systems.

The structure of project supply systems adds to this challenge. As shown in Figure 1.1, adapted from Basu (2011), PDSCs include distinct building blocks across planning and delivery. Layers like quality control and governance interact with these blocks throughout the project timeline. Each relies on timely handovers from the previous phase. When procurement or supplier coordination fails, the effects ripple outward. Logistics are disrupted, and final handover is delayed.

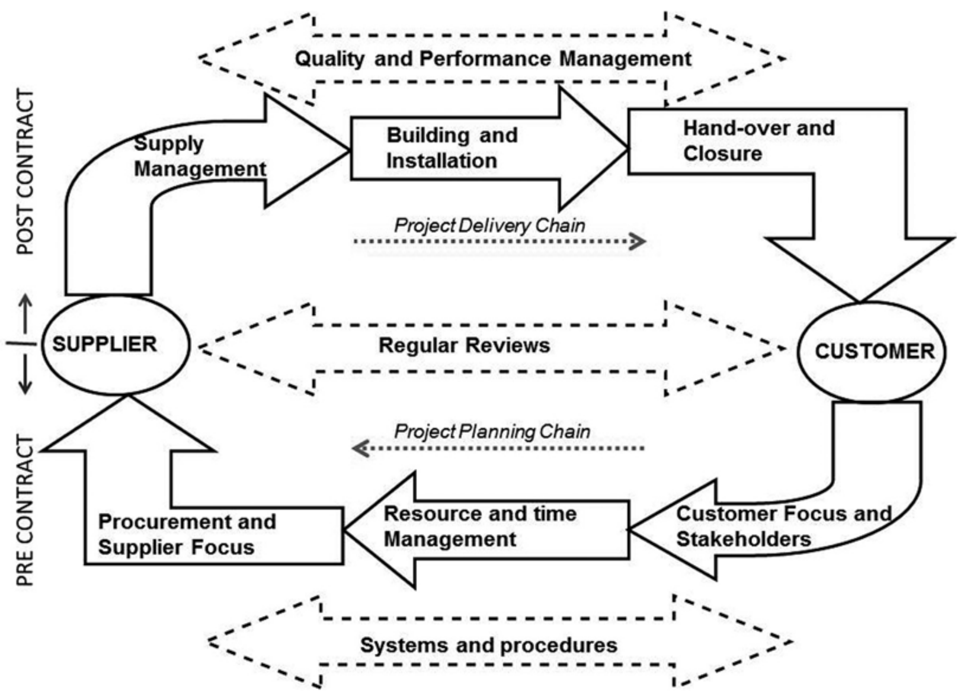

Figure 1.1. Project Supply Chain Building Blocks. Adapted from (Basu, 2011).

In practice, coordinating these flows is often more fragile than it appears. Suppliers may use different internal systems or operate with varying levels of process maturity. Updates are sometimes shared through informal emails, and purchase orders may lack standardized references or version control. Without shared visibility, problems often remain hidden until their impact reaches the project site.

Compounding these coordination issues is how delivery performance is typically measured. Labels like “on time” or “late” provide little insight into reliability. They do not show how consistently a supplier meets expectations or whether patterns of deviation are emerging. Bhattacharyya et al. (2023) argue that delivery deviation offers a more meaningful view, especially in dynamic systems. Their model captures behavioral variance—a key factor in long-term reliability.

Traditional logistics tools do not help much in this context. Concepts like Economic Order Quantity (EOQ) and reorder points assume steady demand and repeatable flows. PDSCs offer neither. Orders are often unique and non-substitutable. When a critical component is delayed, there may be no second opportunity to deliver it without disrupting the project schedule.

In project supply chains, supplier delivery reliability is not a minor issue. It is a structural risk that shapes project cost and control.

1.2 Purpose of the Study

PDSCs are inherently fragile. As discussed earlier, even small deviations in supplier delivery timing can disrupt tightly scheduled milestones. Yet coordination practices in these environments remain largely reactive. Supplier updates are often informal, and delays are typically flagged only after they’ve begun to affect downstream activities. Real-time performance data is limited, and predictive insight is rarely applied.

This lack of foresight creates more than operational inconvenience—it introduces structural risk. A single delayed component can halt critical tasks, while the root cause remains hidden in fragmented systems or outdated status indicators. Malhi (2024) notes that predictive approaches remain underused in Supply Chain Risk Management (SCRM), particularly in complex, multi-actor settings like projects.

Visualization tools offer limited help. Traditional Value Stream Mapping (VSM)[1], though useful in stable manufacturing flows, is not designed to handle uncertainty or supplier responsiveness. Locher (2008) emphasizes its strengths in repetitive environments, but project supply chains rarely offer that consistency.

Meanwhile, AI tools have begun to show potential for delivery forecasting and risk attribution. Culot et al. (2024) point out that most AI applications still focus on stock optimization, leaving supplier-side coordination underexplored. Recent developments—such as delivery deviation prediction (Rezki & Mansouri, 2024) and root cause delay analysis (Bo & Xiao, 2024)—highlight new ways to anticipate problems before they affect the project timeline.

This thesis builds on that emerging potential. It investigates how AI models—when used selectively and tailored to the realities of project delivery—can enhance supplier reliability. Rather than aiming for full-scale deployment, the study adopts a simplified VSM approach to examine a real-world case. The goal is to surface coordination challenges and assess how specific AI model types can be positioned to support smarter, more reliable supply decisions—without requiring major system changes.

The goal is structured improvement. By combining process visualization with AI-supported reasoning, the thesis enables earlier risk detection and more reliable project coordination.

1.3 Research Objectives and Research Question

This thesis was motivated by a practical challenge faced by the case company: improving supplier delivery reliability in a project-driven supply environment. Across several interviews, project stakeholders described how coordination issues often emerge late in the

[1] In this thesis, *Value Stream Mapping (VSM)* refers to the process or method, while *Value Stream Map* refers to the resulting diagram or tool. The abbreviation VSM is only used when describing the mapping process.

process—during readiness or dispatch—when recovery options are limited. Supplier performance is typically tracked manually, and delays are discovered reactively. Performance data exists but is rarely structured to enable proactive response or pattern detection.

The study aims to explore whether AI models—when strategically evaluated and aligned with project coordination flow—can support more reliable supplier delivery in such contexts. Rather than focusing on full deployment, the thesis applies a simplified VSM approach to one real project. This map is used to identify coordination weak points and evaluate which AI model types could provide timely and targeted decision support.

The research is guided by the following question:

> **How can AI models be integrated into project-driven supply chains to improve supplier delivery reliability?**

To address this question, the thesis pursues the following objectives:

- Map the supplier-related delivery flow of a real project using a simplified Value Stream Map tailored to project-driven supply logic.
- Identify where reliability breakdowns occur and how they affect project execution.
- Evaluate suitable AI models based on their ability to support coordination at these points.
- Propose a conceptual framework that integrates these AI elements into a redesigned TO-BE process. This structure supports strategic improvement in supplier coordination and project delivery performance.

These objectives structure the thesis analysis. They define its contribution to supplier coordination and project management within adaptive project supply chains.

1.4 Scope and Limitations

This thesis focuses on supplier delivery reliability within a PDSC, using one real-world case project from the case company's energy division. A simplified VSM approach is used to visualize supplier coordination and identify where delays, gaps, and handovers introduce risk. Instead of system-wide optimization, the study focuses on an Engineer-to-Order (ETO) delivery flow typical of project business environments.

AI models are not implemented in this thesis. Instead, they are conceptually evaluated based on their relevance to coordination issues and their fit with the case organization's context and capabilities. One model—a fuzzy logic–based decision tool—is also explored through a simplified simulation to illustrate its potential as a decision-support tool. The main output is a conceptual framework: a redesigned TO-BE coordination process that integrates AI model roles to support structured improvement in similar project settings.

The scope is shaped by the following constraints:

- Focuses on a single project case, without attempting to generalize findings statistically across industries or divisions.
- Assumes manual supplier tracking and coordination at the case company, limiting the feasibility of real-time AI deployment.
- Relies on the structure and availability of case company data, constraining the evaluation of delivery reliability and limiting access to advanced or behavior-based indicators.

The final section of this chapter explains how the rest of the thesis is organized to answer the research question.

1.5 Structure of the Thesis

This thesis is structured to guide the reader through a logic-driven progression—from identifying delivery reliability challenges in PDSCs to evaluating the potential of AI-supported solutions. Each chapter builds on the last, using a simplified VSM approach as the central diagnostic tool and anchor for AI model positioning.

Chapters 2 through 4 establish the literature foundation. Chapter 2 explores the nature of PDSCs and the root causes of delivery risk. Chapter 3 introduces Lean thinking and VSM, focusing on their application to coordination in project supply environments. Chapter 4 reviews relevant AI models and assesses their potential to improve delivery reliability.

Chapters 5 through 7 form the empirical core of the thesis. Chapter 5 details the research approach and data methodology, showing how the case project and its coordination process were analyzed. Chapter 6 uses mapping and metrics to reveal where supplier delivery breaks down. Chapter 7 responds with a redesigned model that uses AI to improve visibility and guide decisions at known weak spots.

Chapter 8 brings the thesis to a close by summarizing key findings and their strategic significance. It offers implementation recommendations grounded in the case company's operational environment and discusses how AI-supported coordination can strengthen delivery governance. Supporting appendices explain the underlying metric calculations and document the FIS simulation used to validate the TO-BE process redesign.

Chapter 2

Project-Driven Supply Chains and Delivery Reliability

Project-Driven Supply Chains (PDSCs) operate under fundamentally different conditions than traditional supply chains. Each project is a unique undertaking, often designed from scratch and delivered to a fixed timeline. This chapter explores how these characteristics shape supply chain behavior. It also examines why delivery reliability is difficult to maintain and why current risk mitigation strategies often fall short.

2.1 Structure and Characteristics of Project-Driven Supply Chains

Supply Chain Management (SCM) began as a way to link different parts of production and delivery. Traditional supply chains are built for stability. They aim to reduce cost and waste through predictable systems (Sarkis, 2024). Each part of the chain—sourcing, manufacturing, and distribution—works within a continuous flow. Chopra (2019) describes this flow as a coordinated network that meets demand efficiently. These systems are shaped by repetition. Relationships are long-term. Processes are fine-tuned to work again and again.

PDSCs are built differently. They are temporary. Each one exists to deliver a specific project. When the project ends, the supply chain ends with it. Asbjørnslett (2003) describes this model as goal-specific. It does not follow the logic of ongoing production. Instead, it is shaped by the project's schedule and technical requirements. The network includes suppliers and contractors who may never collaborate again. These actors come together only for that project, and for a limited time.

This structure separates project supply chains from traditional ones. Traditional supply chains forecast demand and follow known schedules. Project supply chains begin with a signed order and work toward unique milestones (Gosling & Naim, 2009). As Cannas and Gosling (2021) explain, project environments often follow an Engineer-to-Order (ETO) logic, where the product is not fully defined at the start. Design decisions shape procurement and delivery as the project unfolds. These differences are summarized visually in Figure 2.1[1].

Traditional Supply Chain	Project-Driven Supply Chain
Forecast-driven	Order-driven (starts after contract)
Continuous flow	Temporary, milestone-bound
Long-term supplier relationships	One-off supplier networks
Buffer-based risk mitigation	Tight schedules, no buffers
Repeatable processes	Custom, non-repeatable flows
Stable roles and systems	Dynamic roles and fragmented systems

Figure 2.1. Structural differences between traditional and project supply chains.

[1]Figures without a cited source are developed by the author.

The building blocks of a project supply chain follow the stages of the project itself. It starts with planning and ends with handover. Each stage brings in different responsibilities (Basu, 2011). Before the contract, the customer leads. After the contract, the supplier takes over. These handoffs are managed through two parallel chains—one for planning, and one for delivery. Supporting elements like documentation and reviews run throughout. Figure 2.2 shows how these parts are linked across the project timeline.

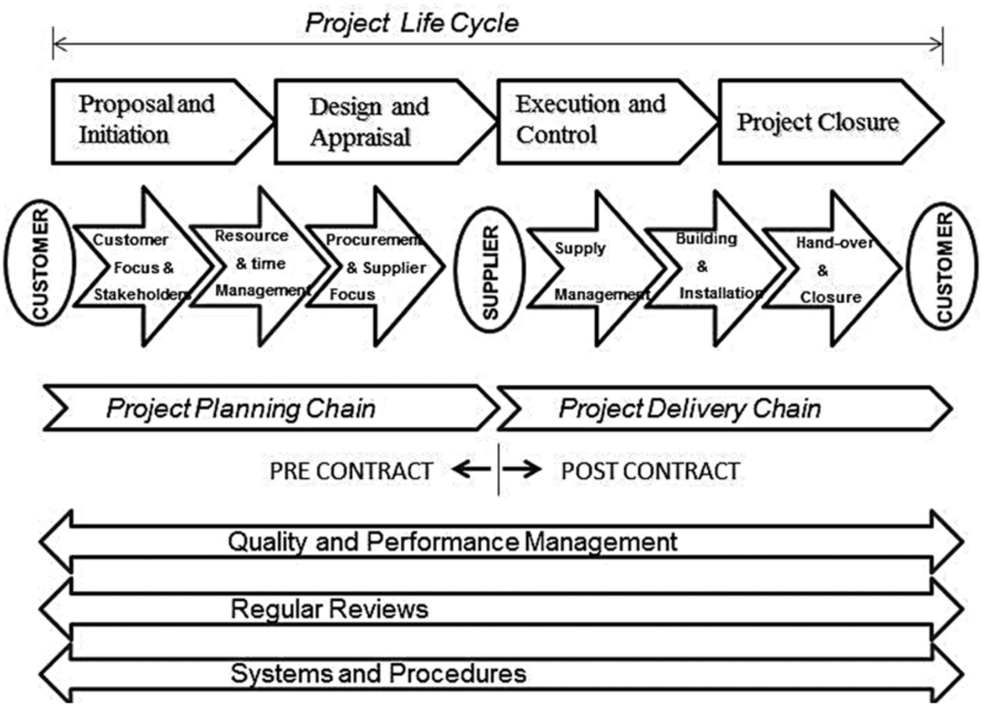

Figure 2.2. Project supply chain building blocks and project life cycle. Adapted from (Basu, 2011).

This structure makes coordination more complex. Each project creates a new system. Roles shift, and systems don't always align. There is little room for habits or routines. What worked once may not work again. That makes reliability a serious concern. One missed delivery can hold up an entire sequence. The next section looks at what reliability means in a supply chain, and why it matters in project delivery.

2.2 Supplier Delivery Reliability in Project Supply Chains

Delivery reliability[2] describes how well a supplier delivers what was promised, when it was needed. It is not just about shipping on time, but about meeting expectations that are often shaped by changing project demands. In project-based environments, poor delivery reliability can delay milestones and drive up project costs (Salmi, 2017). As shown in Figure 2.3, the impact rarely stays local. Pinto et al. (2013) demonstrate how a single supplier delay can disrupt the broader delivery system. This risk grows when there is limited visibility into supplier performance. In practice, delivery reliability is often tracked using simple indicators—such as whether goods arrived by the confirmed date (Tainala, 2023). These metrics help, but they do not explain the cause of unreliability or predict future issues. In project supply chains, reliability is not just a number. It is a condition that determines whether the project stays on schedule.

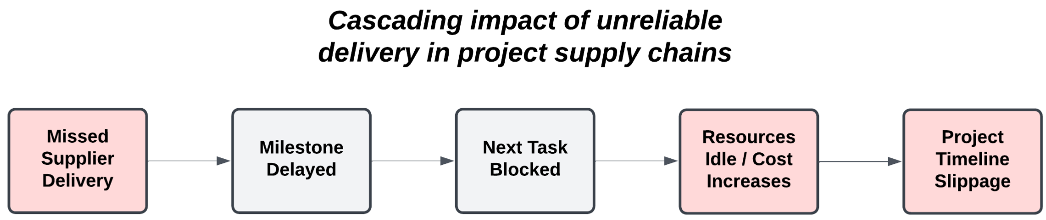

Figure 2.3. Impact of missed supplier delivery in project-driven supply chains.

Delivery reliability is not a new idea. It exists in every supply chain. But in project-driven environments, its role changes. Traditional supply chains can absorb small delays. They maintain buffer capacity and rely on stable contracting practices. Project-based supply chains do not. Every delivery is tied to a specific milestone. If a shipment is late, the next task may not start. In a project setting, reliability is not about improving performance. It is about avoiding disruption.

[2]Delivery reliability refers to the consistency with which suppliers meet the planned delivery date. In this thesis, it is treated both as a performance metric and as a central research focus, examined through real project data and supported by AI-based risk detection.

Delivery reliability is difficult to maintain in project supply chains, even when all actors intend to perform. The problem is not always disruption. Sometimes it is structure. Sarafan et al. (2022) point out that project supply networks are decentralized. Each supplier operates with its own tools and internal priorities. There is little continuity across projects. Coordination depends on timely knowledge exchange, not repeatable systems. Chen and Lee (2017) add that incentives are rarely aligned. No actor is fully responsible for cross-chain timing. This weakens accountability. Forecast error adds another layer. Li and Dörfler (2024) show how minor demand shifts can trigger delivery volatility. Without buffers or stability, the supply chain reacts instead of adjusts. Ogundipe et al. (2024) find that unclear specifications and fragmented systems often delay supplier responses. These conditions make reliability fragile. In project environments, failure often comes from how the system behaves—not just from supplier mistakes.

Most supply chains attempt to manage delivery reliability through internal procedures and performance tracking. In project environments, these efforts often fall short. The systems are not designed to handle shifting timelines or one-off supplier arrangements. Even when delivery is monitored, consistency remains difficult to achieve. This is not always due to lack of planning. Often, the root causes lie deeper—in how project supply chains are structured and how risks emerge across the delivery process. The next section explores these risks in more detail.

2.3 Risk Sources in Project-Driven Supply Chains

Supply chain risk refers to the potential for disruption that affects an organization's ability to deliver on its objectives. Manners-Bell (2023) defines supply chain risk as the chance that a disruptive event will materially compromise customer service or business continuity. It can also affect broader social and environmental responsibilities. The scope of risk is not limited to physical damage or delay. It includes any event that disrupts process flows or coordination mechanisms across the supply network. Waters (2007) adds that risk spans a wide spectrum—from minor disruptions to complete system failure. In PDSCs, these risks are amplified by temporary operating structures and strict milestone dependencies. This section examines where those risks come from—starting at the macro level and moving inward. These risk categories are shown in Figure 2.4.

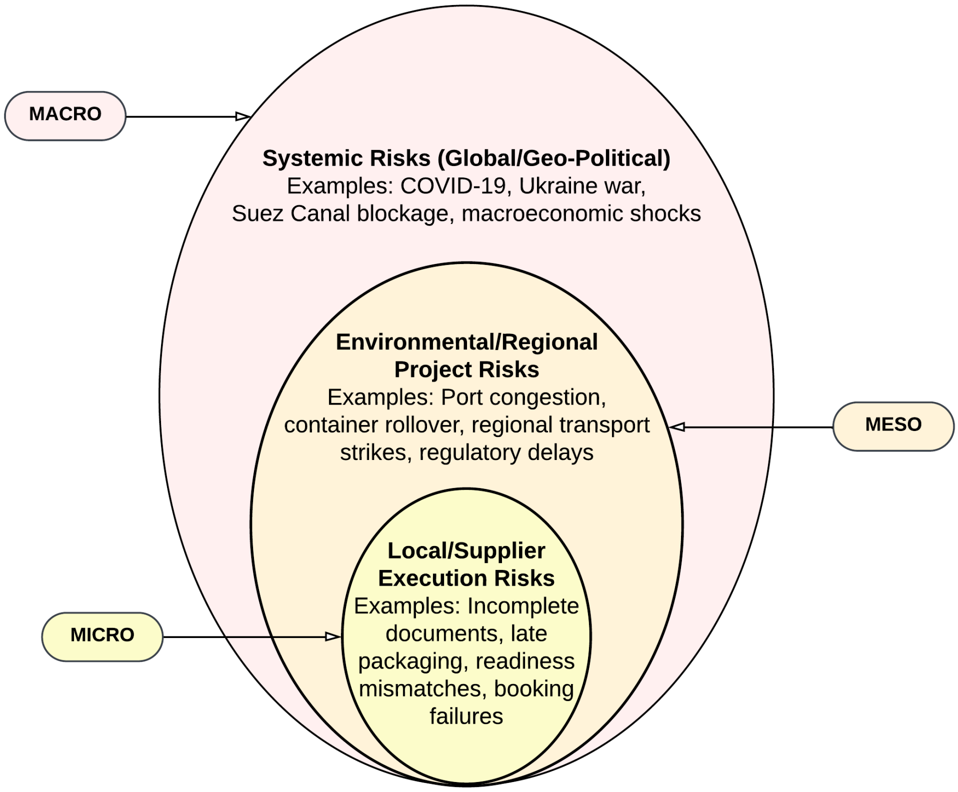

Figure 2.4. Layered risk sources in project-driven supply chains.

At the micro level, disruptions emerge from localized, project-specific conditions. Tran et al. (2025) explain that issues such as port congestion and container rollover can delay cargo even after on-time dispatch. Similarly, Giraldo (2024) observes that regional disruptions—like waterway blockages, regulatory restrictions, or environmental bottlenecks—can destabilize otherwise stable delivery flows. These fall within what some scholars describe as the meso layer, situated between global shocks and local execution failures. Such disruptions are not always captured by standard delivery metrics but can significantly affect coordination and milestone adherence. Fortes et al. (2023) emphasize that ETO projects are especially vulnerable to coordination failures. These often arise from incomplete documentation or delays in packaging and readiness at supplier sites.

These risks were observed in real-world project settings. In several cases, suppliers confirmed shipments despite missing documents or incomplete packing. This forced downstream teams into reactive adjustments, creating avoidable delays and coordination gaps. These real-world examples mirror the literature and underscore how small failures at the micro and meso levels can escalate without early detection.

Many of these risks remain invisible until it is too late. Companies rarely notice problems before they disrupt operations. According to Heckmann et al. (2015), risks stay hidden because information flows are fragmented. Each part of the supply chain sees only a small piece of the picture. Gurtu and Johny (2021) add that even minor disruptions quickly escalate in complex networks, where small issues can trigger large-scale delays. Traditional risk management compounds this problem. Fan and Stevenson (2018) highlight that most methods identify issues only after they occur, leaving little time to adjust. By the time a delay is recognized, it may have already impacted timelines or resource planning. In PDSCs, this fragility makes proactive risk management both necessary and difficult. These limitations have led many organizations to rely on mitigation strategies like buffering, static segmentation, and manual coordination. The next section examines how these methods work—and why they often fall short in project-driven environments.

2.4 Traditional Mitigation Strategies and Their Limits

Traditional risk mitigation strategies aim to reduce the likelihood or impact of supply disruptions. These include actions like buffering, static supplier segmentation, and manual coordination routines. Each offers a way to maintain project continuity when delays or uncertainties arise. Waters (2007) highlights that mitigation often involves structural responses—such as adding inventory, creating alternative routes, or shortening supply lines. Manners-Bell (2023) adds that these approaches are reactive. They manage consequences, not causes. Wieland and Wallenburg (2012) reinforce this view. They show that mitigation strategies can improve robustness or agility. But if poorly aligned, they may lower performance or create new risks. In complex project environments, these legacy methods are showing their limits. They offer insurance—but not insight.

2.4.1 Buffering Strategies

One of the most common methods in traditional supply chains is buffering—used to absorb uncertainty and maintain flow. These buffers typically take the form of resource buffers or time slack. Their purpose is to protect operations from variability in demand, supply, or process performance. Malhotra and Krajewski (2022) outline how such buffers are used in frameworks like Drum-Buffer-Rope to shield bottlenecks and ensure continuous output. In steady, high-volume environments, this logic provides stability and predictability.

In PDSCs, however, buffers are harder to justify. Projects must meet fixed milestones within tight budgets. Holding excess inventory may not be feasible, and slack time is rarely available. Schönsleben (2022) highlights how buffering in these contexts can create a false sense of control. Instead of solving underlying coordination problems, it often conceals them. The result is a process that appears protected but remains vulnerable to disruptions.

Kouvelis et al. (2023) provide further evidence of these limits. Their study shows that even when inventory and time buffers are applied in project supply chains, material shortages still persist. The dynamic nature of projects—where requirements shift, suppliers vary, and delays compound—renders static buffers insufficient. This reinforces the broader challenge: while buffering remains a common strategy, it offers limited risk mitigation in project environments without deeper coordination and visibility.

2.4.2 Static Supplier Segmentation Models

Static supplier segmentation is a common way to reduce risk and focus attention where it matters most. The Kraljic matrix is one of the most widely used tools. It classifies suppliers by financial impact and supply risk, offering a structured foundation for procurement planning (Mandl, 2023). While effective in stable environments, this matrix has limitations in PDSCs. A supplier seen as low-risk in one project may become a bottleneck in another due to shifting designs, documentation issues, or last-minute packaging delays. These dynamics make static segmentation unreliable, as supplier risk is rarely consistent across varying project scopes.

More adaptive approaches have been proposed to address this issue. O'Brien (2014) suggests scoring suppliers based on their conduct and strategic fit—allowing for dynamic reassessment as conditions change. Gergely (2025) supports this evolution, noting that modern procurement systems are beginning to enhance static models with real-time performance data. These systems use digital tracking to create segmentation profiles that reflect actual delivery behavior rather than assumptions set at the start of a project.

In milestone-driven environments, supplier roles shift too quickly for static models to keep up. Segmentation must evolve with the project. Traditional tools provide a starting point, but project reliability demands more flexible methods.

2.4.3 Manual Coordination Routines

Perhaps the most widespread—and telling—mitigation strategy is manual coordination. At the case company, this takes the form of spreadsheet tracking, regular check-ins, email chains, and buyer-led follow-up. Each project involves dozens of such actions, from confirming readiness details to pushing for packing lists to arrive on time. In practice, this amounts to personalized control over a system that resists formal structure.

These routines function as an informal safety net. They handle late updates and missing information by relying on persistence and interpersonal relationships. But they also come at a cost. As Fugate et al. (2006) note, such practices are resource-intensive and heavily reliant on individual diligence. Coordination becomes reactive by design. Delays are often discovered only when it is too late to adjust without disruption.

This pattern is not unique. Kache and Seuring (2017) highlight how many supply chains still depend on manual routines due to fragmented systems and low digital readiness. Manual tracking fills the gaps, but it lacks visibility and scalability. Fabbe-Costes et al. (2008) show that even when logistics partners are involved, integration is often limited. Coordination falls back on people, not systems.

Despite their differences, these strategies share a critical limitation: they detect problems after they've already materialized. They manage delivery uncertainty, but only once it becomes visible. None offer a proactive mechanism for early detection, let alone prediction. This is not a criticism of the tools themselves—they were built for different times, under different assumptions. But it does highlight the growing gap between what current project supply chains need and what existing mitigation methods can deliver.

Table 2.1. Traditional Risk Mitigation Strategies in PDSCs – Strengths and Limits.

Strategy	**Typical Use in Traditional Supply Chains**	**Limitations in Project-Driven Supply Chains**
Buffering	Adds inventory, time, or capacity buffers to absorb disruptions and maintain flow	Infeasible due to fixed milestones, limited space, and false sense of control; often hides deeper coordination issues
Static Supplier Segmentation	Categorizes suppliers by risk and value using structured procurement models	Fixed segmentation models fail to capture dynamic roles; performance shifts across projects, requiring real-time behavioral data
Manual Coordination	Uses email, spreadsheets, and buyer-driven follow-up to resolve delays and track updates	Labor-intensive, reactive, and prone to visibility gaps; does not scale in multi-supplier environments

Table 2.1 summarizes the strengths and limitations of these traditional mitigation strategies, contrasting their original intent with the realities of project-driven environments.

These constraints help explain the persistence of delivery delays, even in otherwise mature organizations. What today's project environments require are tools that expose risk before it turns into failure. This means moving beyond static assessments and reactive routines. This need forms the basis for the next chapter, which examines how value stream mapping and process visualization have been used to improve supply coordination in project settings.

Chapter 3

Lean Thinking and Value Stream Mapping in PDSCs

This chapter introduces Lean thinking and its relevance to Project-Driven Supply Chains (PDSCs). It begins by outlining Lean's foundational principles and then focuses on Value Stream Mapping (VSM) as a core method for improving visibility and coordination. The chapter explains how VSM must be adapted to fit the dynamic nature of project environments and presents the rationale for using a simplified version in this thesis.

3.1 Introduction to Lean Thinking

Lean thinking began with the Toyota Production System (TPS). It was developed after World War II to help Toyota operate with limited resources. The goal was to remove waste and reduce lead time. Improving quality was also a key focus. As Liker (2021) explains, TPS was not a toolkit—it was a management philosophy that shaped how the company made decisions. Over time, this thinking spread beyond Toyota. Helmold et al. (2022) point out that lean evolved into a strategic approach used across many industries. It shifted focus from internal efficiency to improving coordination between suppliers, project teams, and customers.

Lean thinking is based on five core principles. The first is to define what creates value from the customer's point of view. The second is to identify every step involved in delivering that value. These steps form what is called the value stream. The third is to ensure that this value flows smoothly without interruptions. The fourth is to let the customer pull value as needed, rather than pushing it forward in advance. The fifth is to keep improving the process continuously. Womack and Jones (1996) introduced these principles to help organizations focus on system-wide flow instead of isolated tasks. Hüsselmann (2023) shows how these ideas can guide coordination and handovers in complex projects where many actors are involved.

Lean thinking was first applied in manufacturing, but its use has expanded. Today, it is used in services, logistics, and full supply chains. The objective remains to streamline processes and improve coordination in pursuit of greater value. Keyte and Locher (2016) explain that Lean tools like VSM can be adapted to manage cross-functional processes and information flows. This is especially helpful in complex environments where many teams or suppliers are involved. Christopher (2022) adds that Lean plays a key role in improving supply chain performance.It helps companies respond more quickly to changes. It also supports better coordination and delivery consistency.

PDSCs have different challenges than standard production systems. They often deal with one-off orders and shifting supplier timelines. This makes coordination and visibility more important than speed or volume. Saverio et al. (2021) show that Lean can still work in these environments if it is adapted to project realities. Companies in the ETO sector have used Lean to improve planning and reduce delivery delays. Schulze and Dallasega (2024) further show that Lean can mitigate typical ETO inefficiencies—such as waiting and coordination delays—when adapted to the high variability and low repetition of project settings.

Figure 3.1 illustrates how Lean principles extend across the supply chain, emphasizing value flow from multi-tier suppliers through enterprise operations to end customers. This perspective frames Lean as a coordination tool, not just a production method. It reinforces Lean's role in addressing delivery bottlenecks across supplier networks.

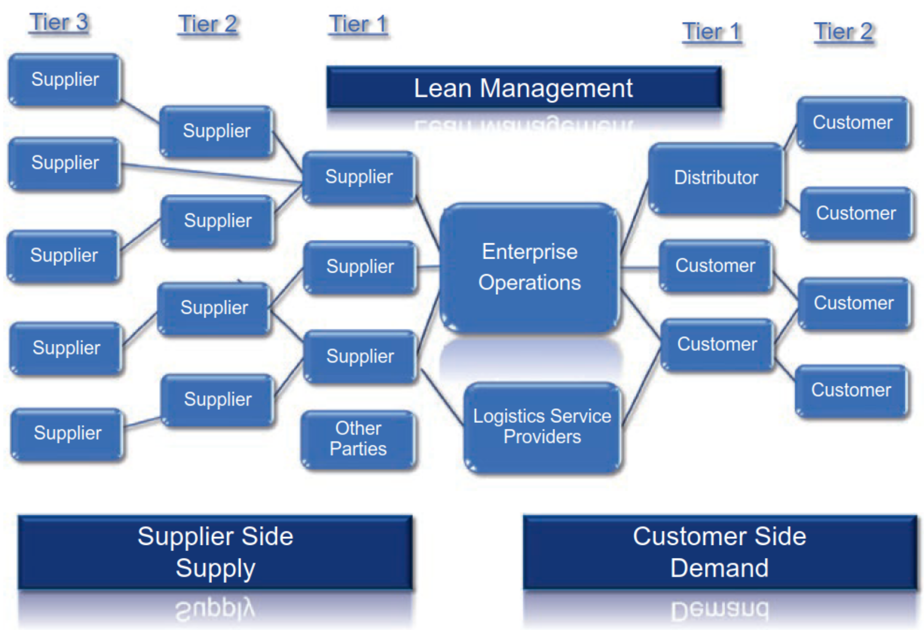

Figure 3.1. Lean management across the supply chain. Adapted from (Helmold et al., 2022).

This view also supports the use of Lean tools—such as VSM—to create visibility across complex project flows. The next section introduces VSM as a practical method for mapping such coordination.

3.2 What is Value Stream Mapping?

VSM is a tool used in lean thinking to visualize how work flows through a process. Its purpose is to separate value-adding activities from those that create waste and delays. Womack and Jones (1996) introduced the concept of the "value stream" to describe all the steps needed to deliver a product or service to the customer. Mapping this stream helps organizations see where time is lost and where processes break down. K. Martin and Osterling (2014) emphasize that VSM creates a shared understanding of how work moves across teams and systems. It provides a clear starting point for identifying improvement opportunities.

A typical Value Stream Map outlines process steps and tracks the flow of materials and information. It also presents key metrics such as lead time and inventory levels. Visual symbols are used to show how tasks are performed, how decisions are made, and where information is exchanged. Seth et al. (2017) explain that VSM visualizes material and information flows to help teams identify waste, assess process performance, and improve coordination. King and King (2017) add that the structure of a Value Stream Map can be adjusted to match different types of processes. In more complex environments, it becomes especially useful for highlighting hidden hand-offs and coordination gaps.

The main benefit of value stream mapping is improved visibility. It reveals how work actually flows, not just how it is assumed to flow. This helps teams identify bottlenecks and unnecessary steps that are often hidden in day-to-day operations. Keyte and Locher (2016) note that VSM supports alignment across departments by creating a shared view of the process. El Kihel et al. (2022) emphasize that this shared understanding is critical in distributed environments where materials and information must be tightly coordinated. The map acts as a foundation for targeted improvements.

Although VSM was first used in manufacturing, it has proven useful in many other contexts. Locher (2008) shows that VSM applies beyond manufacturing by focusing on task and decision flow in service or project environments. The structure of the map stays the same, but what it captures changes. Instead of tracking production steps, it can visualize supplier handoffs or coordination gaps. Suárez-Barraza et al. (2016) argue that VSM can be extended to supply chains, where it highlights delivery risks and communication breakdowns between organizations. This flexibility makes it a strong tool for project-based supply chains.

In traditional applications, VSM assumes a relatively stable and repeatable process. The tool works best in linear flow environments. Its effectiveness depends on the ability to calculate takt times and measure inventory buffers. Figure 3.2 illustrates the classical structure. It shows a horizontal sequence of standard steps with synchronized timing and marked inventory points designed for production-focused use. These assumptions have made VSM effective in manufacturing contexts but limit its relevance when applied directly to project-based supply networks.

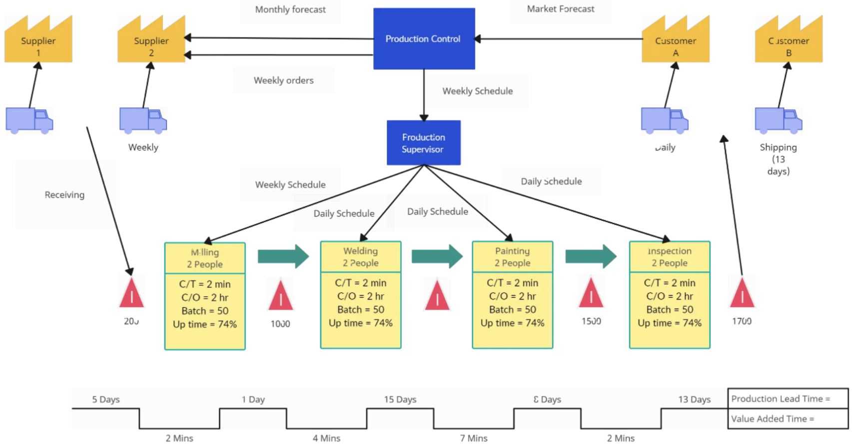

Figure 3.2. Example of a Traditional Product-Based Value Stream Map. Adapted from (Athuraliya, 2022).

While this traditional layout supports stability and standardization, project-driven environments require a shift in what is mapped and how value is defined. The next section explores how VSM can be adapted to visualize supplier coordination in such settings.

3.3 Adapting VSM to Project-Driven Supply Chains

Traditional VSM was designed for environments with stable, repeatable processes. These conditions rarely exist in PDSCs, where flows depend on shifting requirements and planning structured around milestones. Wollert and Behrendt (2023) argue that conventional, static VSM methods lack the flexibility to represent such dynamic settings. Their review highlights the need for modular approaches that separate stable from variable process components. Dal Forno et al. (2014) reinforce this point, identifying instability and limited integration as common problems in VSM applications across complex industries. These challenges show that while the structure of VSM remains useful, its application must be adjusted to reflect the realities of project-oriented delivery systems.

Classical Value Stream Maps are based on several assumptions. These include fixed takt time and the presence of consistent inventory between repeatable tasks (Rother & Shook, 1999). These assumptions do not hold in PDSCs, where flow depends on engineering readiness and supplier availability. In such cases, the goal of mapping shifts from tracking material movement to visualizing coordination between actors. Lindholm (2018) demonstrates this shift by applying VSM to a prefabrication process in an Engineering, Procurement, and Construction (EPC) project. Instead of focusing on production steps, his map captures interactions across functions like engineering, procurement, and supplier dispatch. This shows how VSM can be adapted to highlight delivery reliability and milestone progress without changing its core structure.

Table 3.1. Comparison of Traditional VSM and Project-Driven VSM Characteristics.

Traditional VSM (Product-Based)	**Project-Driven VSM (PDSC)**
Linear, repetitive production processes	Non-linear, project-specific workflows
Emphasis on cycle time, takt time, inventory	Emphasis on delivery deviation, lead time gaps, milestone readiness
Stable demand and fixed schedules	Milestone-driven timelines with shifting coordination needs
Internal process optimization focus	External coordination across suppliers and logistics stakeholders
Static diagnostic tool	Dynamic visibility tool for milestone risk exposure

Table 3.1 outlines the shift in assumptions and design logic that underpins this reoriented VSM approach. Rather than tracking efficiency through time-in-process or work-in-progress metrics, the project-based VSM emphasizes the alignment, or misalignment,

between supplier deliveries and critical project events. What gets mapped is not production rhythm, but delivery impact.

When adapted to complex settings, VSM becomes more than a tool for waste elimination. It supports cross-functional planning, exposes coordination risks, and helps align teams around shared delivery goals. Lee et al. (2021) show that VSM can be tailored to track sustainability indicators and broader strategic outcomes, not just process speed or cost. Bhasin (2012) further emphasizes that in large organizations, VSM gains relevance when integrated with supplier performance and end-to-end visibility. In project-driven environments, this strategic framing helps managers identify weak links in supplier readiness. It also supports clearer role definition and smoother flow across system boundaries.

Adapted uses of VSM have already been validated across multiple industries facing similar coordination challenges. De Steur et al. (2016) show how VSM has been applied in agri-food supply chains to map full-chain flows from producer to consumer, capturing inter-organizational delays and systemic waste. This confirms the tool's relevance in settings where process control is shared among multiple actors. Pekarcíková et al. (2021) also demonstrate that VSM can incorporate non-traditional metrics—such as process lead time variability and bottleneck frequency—especially when supported by simulation. These examples support the thesis approach: using VSM to visualize delivery alignment and supplier coordination without altering its original structure.

These adaptations show that value stream mapping remains applicable even in complex, project-based environments—provided it is used to capture coordination flow and strategic visibility. The next section explains why this tool was selected to analyze supplier-related inefficiencies in the context of the present case project.

3.4 Justifying the Adapted VSM Approach

This thesis does not use a full-scale Value Stream Map. Instead, it applies a simplified version adapted to the realities of a PDSC. The decision was intentional. Full Value Stream Maps demand significant resources—large teams, constant data access, and sustained observation over time. These conditions were not present in the study environment. More importantly, the goal was not to create a textbook model. The goal was to generate useful insights. That required flexibility. It also required a method suitable for rapid validation. Just as importantly, it had to remain practical and easy to update. In addition, the time-limited nature of this thesis and restricted access to key project stakeholders made it impossible to conduct a full-scale collaborative VSM workshop. These practical constraints reinforced the choice to build a researcher-driven map, using available data and interviews. The adapted Value Stream Map serves that purpose. The paragraphs that follow explain why this approach is supported by literature, confirmed by context, and aligned with modern lean thinking.

The literature supports adapting Value Stream Maps to the realities of dynamic or resource-limited environments. Horsthofer-Rauch et al. (2022) highlight that traditional VSM, while effective, struggles in high-variance settings due to its static nature and manual data demands. They argue that digital or hybrid methods—those that combine manual insight with system data—offer a viable evolution. In such models, simplification is not a weakness. It is a response to complexity. They highlight that tools like process mining, clustering, and system-derived metrics can extend VSM's relevance without abandoning its core structure. These adaptations are especially suitable for settings where full automation is not yet possible but continuous improvement is still needed.

These limitations were confirmed through stakeholder interviews. Core supply processes are still tracked manually. Purchase Orders (POs) often lack item-specific codes. Delivery readiness is confirmed through email or direct calls. Systematic logging of defects or delays is rare, especially at the project site. Real-time data integration is not available.

Inventory is monitored at the container level, not at the part level. In this environment, building a full-scale Value Stream Map would not only be impractical—it would risk misrepresenting how the supply flow actually works. The adapted Value Stream Map reflects what the company can see, measure, and improve today.

Despite its simplification, the adapted Value Stream Map delivered value. It mapped the real sequence of supplier coordination and highlighted key delays and system gaps. During interviews, the strategic purchaser confirmed its practical relevance. It helped clarify which steps cause friction and where improvement is possible. It also provided a shared view across roles—connecting procurement, logistics, and transport in one structure. Most importantly, it created a foundation for simulation. This allowed the thesis to go further: from description to redesign, from analysis to action.

This direction reflects a broader shift in VSM practice. As Teriete et al. (2022) emphasize, modern VSM is moving toward hybrid models—manual where needed, digital where possible. Their framework introduces an event-based architecture that decouples data collection from processing, enabling continuous and scalable VSM updates. This thesis follows that path. The adapted Value Stream Map is not a shortcut; it is a step toward integration. It enables targeted AI applications, aligns with lean principles, and prepares the company for gradual digitalization. In this way, the Value Stream Map serves both as a snapshot and as a launch point for transformation.

Chapter 4

AI Applications for Supplier Delivery Reliability

This chapter reviews the role of Artificial Intelligence (AI) in improving supplier coordination and delivery reliability within Project-Driven Supply Chains (PDSCs). It identifies underutilized AI opportunities and evaluates relevant models for forecasting, segmentation, readiness evaluation, and root cause detection. The aim is to connect proven AI capabilities with the practical constraints of project-based environments.

4.1 Introduction

AI has gained increasing attention in supply chain research, especially as firms seek more adaptive and predictive capabilities. While many applications focus on areas like production and demand planning, supplier coordination and delivery reliability remain underexplored domains for AI deployment. Culot et al. (2024) emphasize that despite high expectations, real-world adoption of AI in supply chains is still limited and often confined to pilot phases, particularly outside of core production functions. Cannas et al. (2024) confirm that sourcing and delivery processes are often overlooked, with most AI initiatives targeting plan and make activities. This reveals a gap between technological potential and practical use in supplier coordination and delivery operations.

Although Riahi et al. (2021) show that sourcing and delivery are gaining attention in AI research, a range of promising methods remain underexplored. This chapter examines how selected AI models can support supplier segmentation and delivery coordination. Clustering, as one example, remains underutilized in these areas. Its purpose, however, is clear. Rashid (2025) emphasizes the importance of segmenting suppliers based on delivery performance to improve project-driven reliability.

The models reviewed in this chapter are grouped by function. Each addresses a specific delivery coordination need. This structure reflects how AI can be applied step by step, not all at once. The grouping also follows what is feasible in the case company. Some models are ready to use. Others are more forward-looking. Each section now explores one application area and the AI models suited for it.

4.2 Delivery Forecasting Models

In PDSCs, delivery reliability is often compromised by unexpected delays. These disruptions are rarely buffered by inventory, which makes their impact more visible and costly. As supply chains shift toward data-driven decision-making, forecasting models have become central to anticipating such deviations before they materialize.

Recent literature reflects this shift, with a growing emphasis on machine learning models designed to predict delivery risks. Davuluri (2023) shows how time series and classification models are used to forecast delivery reliability and support logistics planning. Gradient boosting models have gained traction for this purpose, especially in cases where supplier data and transport variability are available. Among these, Light Gradient Boosting Machine (LightGBM) stands out due to its efficiency and strong predictive performance.

LightGBM was introduced by Ke et al. (2017) as a gradient boosting framework optimized for speed and accuracy on large datasets. Khiari and Olaverri-Monreal (2020) demonstrated its effectiveness in predicting delivery delays in postal logistics using structured trip-level data. Garg et al. (2025) confirmed similar performance in food delivery, where LightGBM outperformed other models by learning from geospatial and real-time contextual features. Separately, Sani et al. (2023) used LightGBM to predict backorder risk based on lead time and supplier performance. The model proved effective in volatile sourcing conditions.

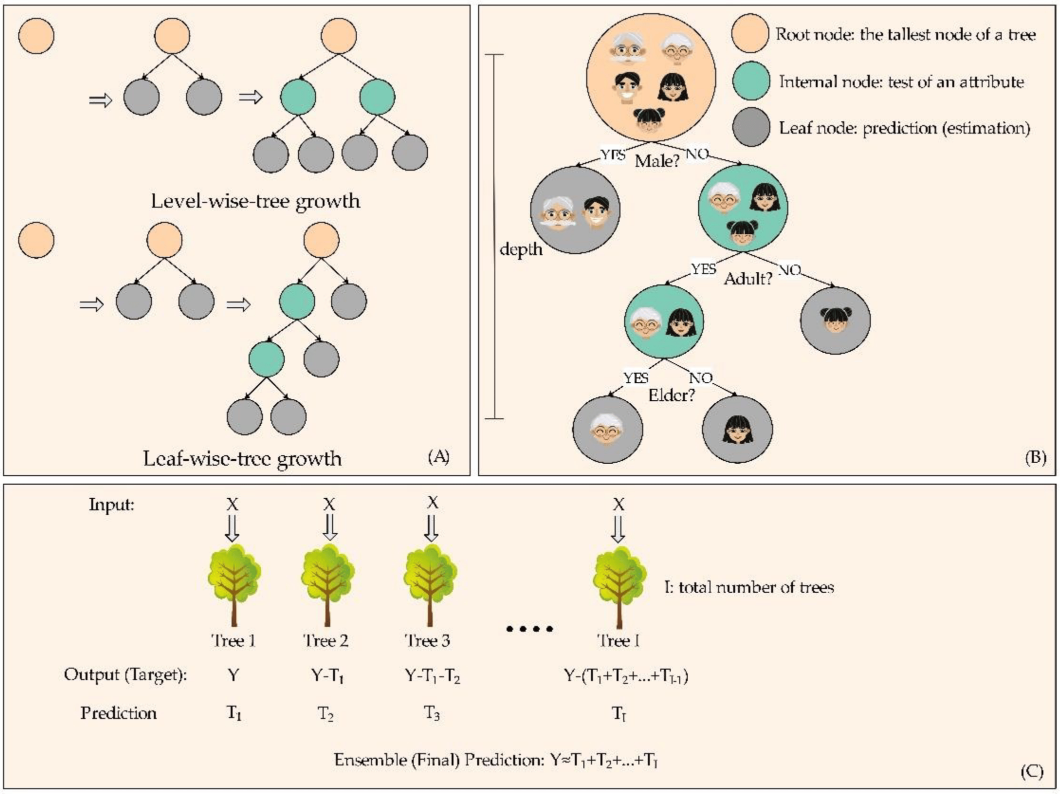

Figure 4.1. Structure of the LightGBM model showing level-wise vs. leaf-wise tree growth and the boosting process. Adapted from (Gan et al., 2021).

Figure 4.1 illustrates the structure and ensemble logic of LightGBM, including its unique leaf-wise tree growth method. This architecture supports both speed and accuracy. Growing trees leaf-wise rather than level-wise, LightGBM reduces error more efficiently with fewer iterations. It is also open-source and actively maintained, making it easy to experiment with using real case data. For the case company, this makes LightGBM a practical first step. It is both lightweight and compatible with Excel-structured delivery data, while remaining easy to interpret.

Beyond LightGBM, alternative models such as Categorical Boosting (CatBoost) and Extreme Gradient Boosting (XGBoost) have also been explored in the literature. Malhi (2024) shows that CatBoost performs well when categorical and historical features are combined to forecast detailed delivery deviation patterns. Similarly, Li (2024) demonstrates that Artificial Neural Networks (ANNs) can be used to model supplier variability and improve responsiveness by capturing nonlinear patterns in historical performance data.

Delivery risk is not limited to suppliers. Port delays and container rollovers also cause disruptions. These events often follow predictable patterns—seasonal congestion, missed vessel slots, or trade lane bottlenecks. Recent studies show that Machine Learning (ML) can forecast vessel arrival times and port congestion using Automatic Identification System (AIS) data and historical patterns (Chu et al., 2024; Mekkaoui et al., 2022). Models like XGBoost and Neural Networks outperform static Estimated Time of Arrivals (ETAs) and help planners act earlier. These tools are not yet used by the case company but could extend supplier delay models to the transport layer.

Despite the growing variety of models available, LightGBM remains a preferred choice due to its performance on tabular supply chain data and lower computational demand. These forecasting models lay the foundation for proactive coordination by identifying potential delivery failures early. This gives planners time to adapt before delays cascade across the project timeline.

4.3 Supplier Segmentation Models

In PDSCs, supplier performance often varies significantly across projects and contexts. Identifying hidden performance patterns supports targeted decision-making and more efficient resource use. Instead of relying solely on predefined risk scores, clustering models offer a data-driven way to segment suppliers based on actual behavior.

Unsupervised learning methods, particularly K-means and Density-Based Spatial Clustering of Applications with Noise (DBSCAN), are frequently used in the literature to group suppliers based on delivery reliability and operational behavior. Ünvan (2021) and Tiwari et al. (2023) both demonstrate the use of clustering techniques in categorizing suppliers within procurement and logistics chains. Albariqi et al. (2025) and Rahiminia et al. (2023) extend this application by linking clustering with supplier evaluation strategies that incorporate either sustainability or operational performance criteria.

Lahtinen (2021) provides practical evidence from procurement, using clustering to group material suppliers based on reliability and historical delivery trends. In a similar context, ul Husna et al. (2024) apply K-means to structure order allocation strategies, showing that segmentation can directly improve decision-making in supplier selection and workload distribution. Figure 4.2 summarizes the standard K-Means process used to iteratively group suppliers based on similarity in performance metrics.

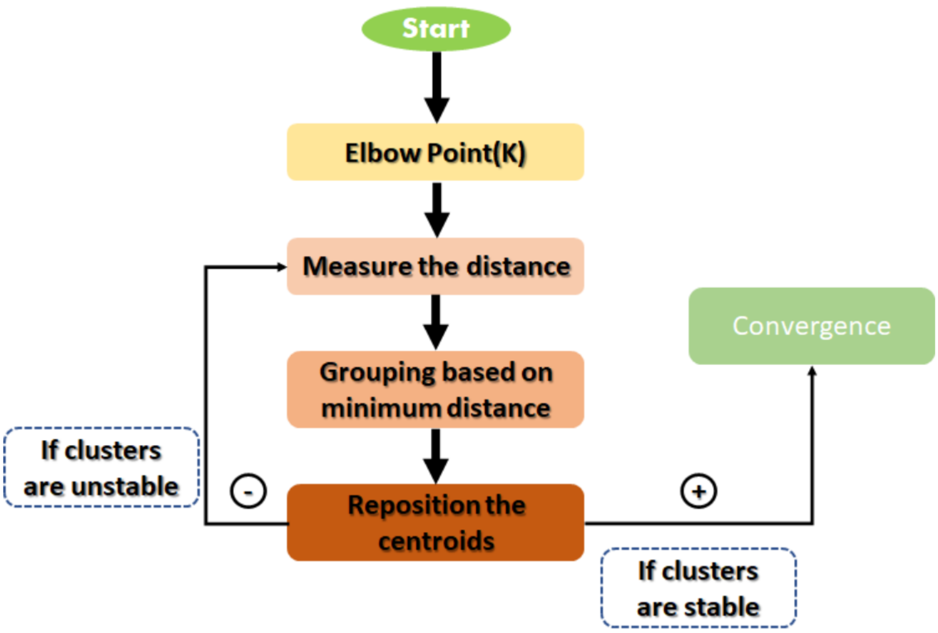

Figure 4.2. Iterative process of K-Means clustering. Suppliers are grouped based on distance to centroids and reassigned until cluster stability is reached. Adapted from (Towards Machine Learning, 2021).

While clustering models do not explain why a supplier performs poorly, they can flag which suppliers consistently deviate from expected behavior. This makes them valuable in post-delivery analysis, where escalation or corrective actions need to focus on the right subset of suppliers. Mavi et al. (2023) and Gidiagba et al. (2025) confirm this use, showing how Clustering supports follow-up strategies in supplier risk and delivery management.

In the context of this thesis, clustering is explored not as a selection tool but as a diagnostic layer that highlights recurring delivery issues and performance trends after shipments are completed.

4.4 Readiness Evaluation Models

In project-based supply chains, delays often arise not from long lead times but from a lack of shipment readiness at dispatch. Readiness depends on signals like packaging activity or supplier responsiveness—factors that are rarely standardized or easy to quantify. Conventional models struggle with these inputs. Jain and Singh (2020), as well as Tavana et al. (2024), show that FIS models are better suited for this kind of semi-structured, expert-driven information. This section explores how FIS can support readiness evaluation when traditional tools fall short.

FIS models provide a structured way to handle such semi-quantitative or expert-driven inputs. Unlike binary classification models, they can process linguistic variables and partial information to produce interpretable readiness scores (Parveen et al., 2020). This allows decision-makers to assess shipment risk even when data is fragmented or subjective.

Sazvar et al. (2022) demonstrate the use of a two-stage FIS model to evaluate supplier readiness under disruption. Their system combines delivery capability, responsiveness, and internal process status to generate a composite readiness score. Lima Junior et al. (2021) apply similar logic to assess supplier performance based on hesitant or incomplete inputs, reinforcing the value of fuzzy models in uncertain environments.

In practical terms, FIS models can be built using internal operational indicators that are already available. These include Systems, Applications, and Products in Data Processing (SAP) booking data and operational signals, such as packaging milestones and supplier responsiveness, which help infer dispatch intent and engagement. Each of these inputs provides partial visibility into shipment status. FIS models offer explainable outputs and do not require full integration with external systems. This makes them a practical first step toward predictive coordination (Ohja et al., 2019).

Figure 4.3 shows the standard architecture used to structure such fuzzy rule-based models.

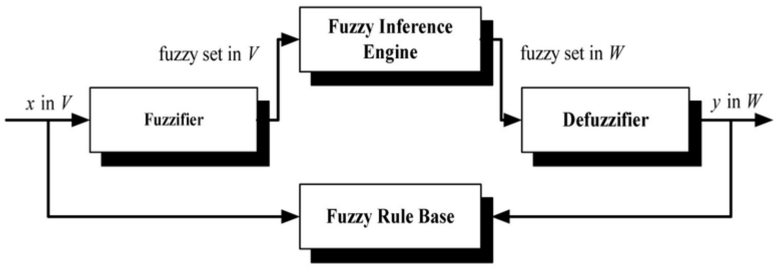

Figure 4.3. Structure of a Mamdani-type Fuzzy Inference System (FIS). This standard logic framework is applied in this thesis to evaluate shipment readiness from semi-structured inputs. Adapted from (Park et al., 2014).

For the case project, shipment readiness evaluation through FIS was conceptually explored as a way to support early risk detection without depending on fully digitized workflows.

4.5 Root Cause Detection Models

While forecasting models help predict when delivery issues may arise, they often do not explain why. In complex supply networks, root cause analysis is difficult. It often fails because of fragmented data and reliance on expert-dependent processes. These challenges are also seen in production systems (Ito et al., 2022).

Recent research explores two advanced approaches to this problem: causal inference and Graph Neural Networks (GNNs). Bo and Xiao (2024) propose combining Reinforcement Learning (RL) with causal attribution to trace the source of delay across different supplier and process nodes. Their model learns which factors repeatedly precede disruptions and assigns causal weights to each factor, providing not just prediction but targeted explanation.

GNNs offer a complementary approach by modeling the supply chain as a network of interconnected entities. Ahn et al. (2024) and Kotecha and Chanona (2024) apply GNNs to simulate how risks spread through supply networks. This helps project teams visualize how local delays can escalate across supplier or transport layers.

These models are not yet widely implemented in project-based supply chains due to their complexity and data requirements. However, they represent the future direction of supplier risk analytics—moving from prediction to explainability.

In this thesis, such models are acknowledged as emerging tools but were not selected for practical implementation. The focus instead remains on more interpretable and feasible models for current project conditions.

4.6 Summary of AI Models and Literature Applications

The reviewed literature highlights a broad set of AI models applicable to supplier coordination in PDSCs. Each model type addresses a different aspect of the delivery flow, ranging from predictive forecasting to post-hoc segmentation and root cause analysis.

Taken together, these models offer a flexible toolkit for identifying and managing delivery risks. Their successful application depends as much on organizational readiness and data availability as on the models themselves.

Table 4.1. Summary of AI Models and Their Application Areas in Supplier Coordination.

Function	**Model**	**Literature Use Case**	**Key Benefits**	**Feasibility Notes**
Forecasting	LightGBM	Delivery deviation prediction	High accuracy, fast training, good for structured data	Easy to implement; low infrastructure demands
Forecasting	CatBoost	Lead time forecasting with categorical features	Handles mixed data types well	Moderate setup; high accuracy
Forecasting	ANN	Supplier performance prediction	Captures nonlinear patterns	Needs larger datasets and more tuning
Segmentation	K-Means	Post-delivery supplier grouping	Simple, interpretable clusters	Low data prep required
Segmentation	DBSCAN	Risk-based segmentation	Detects noise and outliers well	Requires tuning of density thresholds
Readiness Evaluation	FIS	Shipment readiness scoring from qualitative signals	Explainable; works with expert inputs	Easy to customize; high interpretability
Root Cause Detection	Causal RL	Delay cause attribution	Learns intervention pathways	Complex; not widely applied yet
Root Cause Detection	GNN	Risk propagation modeling	Captures supplier interdependencies	Data intensive; emerging method

Table 4.1 summarizes the reviewed AI models and their respective application areas in supplier coordination. The following chapter builds on these insights to define a practical methodology for selecting and integrating AI models in the case context.

Chapter 5

Methodology

This chapter explains how the research was designed, executed, and validated. It begins by outlining the abductive case logic and design science approach used to develop a practical improvement framework for Project-Driven Supply Chains (PDSCs). The next section introduces the case project and justifies the selection of its coordination process as the unit of analysis. This is followed by a focused account of how data was collected from both system exports and expert interviews, with attention to data organization and scope. To ensure methodological transparency, the chapter also discusses how trustworthiness was established through triangulation, documented logic, and traceable simulation procedures. Finally, ethical compliance and the limited role of AI-assisted tools are briefly outlined. Together, these elements provide the foundation for the results presented in the next chapter.

5.1 Research Design and Integrated Framework

This thesis investigates how AI can support supplier coordination in a PDSC. The objective is not only to analyze a specific case but also to develop a transferable improvement framework that aligns with how project supply chains operate in practice. The study combines case-based inquiry with design science principles to produce both insight and utility. It follows a structured process that moves from literature and field data toward a redesigned coordination model grounded in real project conditions.

The research followed an abductive logic. It began with a question: could AI improve coordination in project supply chains? As the work progressed, the focus shifted. Interviews and data narrowed the problem to supplier reliability and coordination breakdowns. These issues caused real delays in the case project and shaped every design choice that followed. Kovács and Spens (2005) frame abduction as an iterative move between theory and field data, where explanations are developed through gradual reframing. Dubois and Gadde (2002) describe this as systematic combining—an evolving process where case observations reshape the analytical lens. Both approaches emphasize learning through redirection, not hypothesis testing.

A single-case study method was used. The case was drawn from a real Engineer-to-Order (ETO) project in the energy sector. This approach was chosen because the problem could not be separated from its environment. Reliability, in this context, depends on project-specific flow. Case study research is well suited to such settings, where context and phenomenon are deeply linked (Yin, 2017). The study also followed design science principles (Hevner et al., 2004). The aim was to generate both insight and utility by building artifacts—such as the AS-IS and TO-BE Value Stream Maps—that help structure decisions and expose coordination problems.

The research did not test models in isolation. It combined literature with field interviews and company data to build something grounded. Each step was shaped by what the project revealed. Each method, metric, and model was chosen because it fit the case. The goal was not technical complexity. It was clarity. A way to expose weak points in coordination and show how they could be improved.

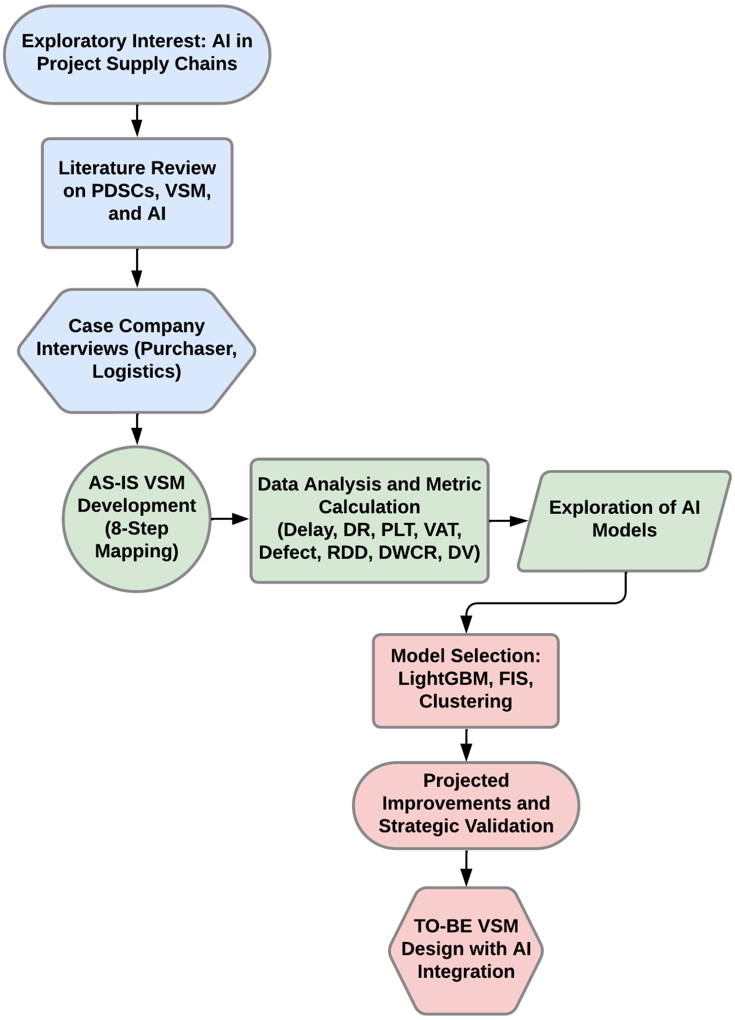

Figure 5.1. AI-Supported Framework for Coordination Redesign in Project Supply Chains.

Figure 5.1 shows the full process. It starts with theory and interviews, moves through mapping and metric analysis, and ends in a redesigned process. Each phase added structure. Each decision was based on real gaps in coordination. What began as a research path became a framework[1] for redesign. Not just for this project, but for others like it.

The framework is modular. It can be reused by companies without full automation or complex systems. Each part—mapping, metrics, models—can be adapted to local needs.

[1]Relevant contributions include Lean-based VSM extensions for supply chain coordination (J. W. Martin, 2007; Suarez-Barraza et al., 2016), predictive applications of AI in delivery performance (Farooq & Yen, 2024; Ferreira & Reis, 2023), and segmentation methods for supplier prioritization (Bernd, 2022; Nasrollahi et al., 2021; Patrucco et al., 2022).

What matters is the logic: first create visibility, then support better decisions. The next section introduces the case project. It explains why this environment provided a realistic setting to apply the framework and study supplier coordination in practice.

5.2 Case Context and Unit of Analysis

The case project analyzed in this study was executed by the case company's Energy business unit. The unit operates in an ETO model. Each delivery is built to unique specifications. The supply chain is assembled around the needs of each project. This creates a coordination setting that differs from steady-state operations, making it a strong test case for the framework developed in Section 5.1.

This case was not selected for representativeness but because it exposed actual breakdowns in supplier coordination. Flyvbjerg (2006) emphasizes that information-rich cases offer stronger learning than those designed for statistical generalization. Siggelkow (2007) makes a similar point: carefully chosen cases can clarify how abstract coordination concepts play out under real project pressures.

In this model, supplier coordination is not routine. Delivery flows vary from project to project. Purchase Orders (POs) are often tied to evolving engineering needs. This makes readiness difficult to track. Delays do not stem from production bottlenecks but from fragmented information and late confirmations. Manual follow-ups were frequent. Transport teams had to react at the last minute.

PDSCs differ from repetitive production lines. Each project is shaped by engineering requirements and supplier constraints specific to its delivery context. These conditions evolve over time. Söderlund (2004) argues that such settings reflect the logic of temporary organizations, where task complexity and actor fluidity create unique coordination dynamics. In such environments, supplier performance cannot be reduced to lead time or cost. It requires tailored evaluation logic that reflects the volatility of engineering-driven delivery conditions (Caiado et al., 2021).

System data supported these observations. Delivery logs in SAP and Power Business Intelligence (PowerBI) showed timing mismatches between supplier confirmations and actual dispatch. The pattern was not random. It revealed a coordination gap between expectation and execution.

Together, these insights narrowed the research focus. The unit of analysis became the end-to-end coordination process—from PO confirmation to shipment release. This decision aligns with what Winch (2014) calls a temporary configuration of permanent organizations. It highlights not only project-specific flows but also how persistent systems and roles affect short-term delivery outcomes.

5.3 Data Collection

This section outlines the data sources used to analyze supplier coordination in the case project. Two primary forms of data were collected: expert interviews and operational system records. These sources enabled the study to trace where coordination issues occurred and provided the basis for evaluating potential improvements.

Semi-structured interviews were conducted with three key stakeholders: the strategic purchaser, the logistics coordinator, and the transport manager. Four sessions were held between January and April 2025. Each interview focused on a different phase of the project, including process mapping, metric validation, and strategic tool alignment. These discussions helped clarify how coordination actually unfolded across procurement, logistics, and dispatch activities. Participants were anonymized in line with Non-Disclosure Agreement (NDA) requirements, and no recordings were stored. This approach reflects what Voss et al. (2002) describe as embedded case data, where expert interviews provide essential context that may not be visible in formal records.

Quantitative data was extracted from the company's SAP system and PowerBI dashboards. This included purchase order logs, delivery confirmations, goods receipt timestamps, shipment delays, and quality notifications. These data points were compiled into eight structured datasets labeled A through H. Each dataset served a specific analytical function, such as calculating procurement lead times, identifying delays, and quantifying supplier defect rates. Supplementary records—such as shipment trackers, transport schedules, and readiness logs—were also reviewed to cross-check gaps in the formal data. A cross-functional process map (`Process_Map_CrossFunctional.pdf`) was reviewed to clarify coordination logic across teams and systems, including how updates were managed in SAP and the project logistics platform. It served as a structural reference for interpreting system records and mapping coordination steps. In addition, the researcher developed a rulebook in Excel format based on internal visual documentation to guide all metric calculations consistently.

Additionally, Dataset D was used to support the readiness simulation in Chapter 7. This included over 5,000 shipment records with fields capturing packaging completion and dispatch clearance. These values were filtered using rule-based logic to test how a readiness scoring system might have performed in real conditions.

Together, these data sources provided a complete view of how deliveries were planned, confirmed, and delayed—and where supplier coordination broke down during execution.

5.4 Validity and Reliability

This section addresses how the trustworthiness of the research was established. While the study follows an abductive case design, care was taken to ensure that its insights rest on methodological clarity and procedural traceability. In line with Gibbert et al. (2008), clarity in construct definition and procedural transparency are essential for methodological rigor in case-based research.

Construct validity was supported through multiple sources of evidence. Core concepts such as delivery readiness and coordination performance were not interpreted loosely. Instead, they were defined using specific system fields from SAP and PowerBI. These were cross-checked against interview feedback and a formal process map that showed how dates and confirmations flowed across teams. In addition, a rulebook was developed in Excel to structure how each metric was calculated. This ensured that the mapping logic remained consistent across datasets, rather than shifting with researcher judgment.

While the constructs were grounded, the interpretation process also followed clear procedures. Some interviews were recorded but not stored; in all cases, detailed notes and typed transcripts were preserved in line with NDA policy. Participants were anonymized, and their roles selected to reflect different parts of the coordination flow. This approach aligns with the credibility and dependability principles outlined by Nowell et al. (2017), where methodological transparency supports trust in qualitative insights.

The analysis also avoided subjective filtering. For example, in the simulation, no data points were manually adjusted. Instead, a rule-based logic was applied to filter readiness signals based on the same fields used by the case company. Although this was a single-case study, the research design aimed for adaptability. The framework was structured to allow similar companies to reuse its logic—particularly the mapping steps, metric structures, and AI model placement. This kind of contextual transfer reflects the trustworthiness criteria outlined by Lincoln and Guba (1985), where confirmability and transferability depend on systematic handling of data and thick process description.

5.5 Ethical and AI Use Considerations

This study complies with the ethical guidelines of the University of Vaasa and the confidentiality agreement signed with the case company. All data was anonymized, stored securely, and processed offline. No identifying or sensitive information was shared with external tools.

AI was used in a strictly supportive role. ChatGPT assisted with language editing and LaTeX formatting. It was also used to summarize selected literature to support synthesis. In each case, the outputs were reviewed and refined before inclusion.

No generative content was accepted as part of the academic work. The role of AI remained editorial, not creative. This aligns with Turnitin standards and university policy.

Responsibility for the thesis, including its structure, methods, and interpretations, remains entirely with the author. This also reflects the broader theme of the study: AI should be used to support human judgment, not replace it.

With the research process complete, the next chapter turns to analysis. It applies the framework developed in this chapter to map the current state and identify coordination gaps in the case project.

Chapter 6

Analysis of the AS-IS Supplier Delivery Flow

This chapter analyzes how supplier delivery was managed in the selected case project. It begins by introducing the case company and the project context to establish why this specific delivery was chosen. The analysis then moves into the strategic framing of the project using the Smart Strategy Board (SSB) and Business Model Canvas (BMC). These tools clarify the delivery structure and stakeholder roles. Together, they provide the foundation for mapping the AS-IS coordination flow and identifying key performance issues.

6.1 Case Introduction

The case company operates in the global energy sector, delivering capital-intensive equipment and life-cycle services for complex infrastructure projects. Each delivery is customized and follows an Engineer-to-Order (ETO) model, with no finished goods inventory. Instead, the company depends on coordinated supplier execution to meet project-specific schedules.

The project selected for analysis involves the delivery of over 100 Megawatt (MW) of fast-ramping capacity to support grid stability in a North American market. The equipment is produced in Europe and delivered through multi-modal container transport. Scheduling is tightly linked to weather conditions, permits, and site readiness, which introduces uncertainty and elevates delivery risk.

This project was chosen due to recurring coordination challenges. Interviews with procurement and logistics staff revealed recurring coordination delays and communication breakdowns. Delivery records confirmed long lead times and inconsistent updates. These issues exposed structural weaknesses in how supplier and transport coordination was managed.

The following section builds on the case context by examining how the delivery model was structured. It introduces two framing tools: the SSB and the BMC. These tools clarify project goals and the structure of supplier coordination. Together, they provide a strategic lens on how the delivery process was designed to function.

6.2 Strategic Framing of the AS-IS Delivery Model

To understand how delivery coordination was structured in the case project, this section analyzes its strategic and operational framing. Two tools are used: the SSB and the BMC. The SSB captures high-level strategic drivers, risks, and stakeholder roles. The BMC then translates these elements into an operational model that defines how value is coordinated across suppliers, logistics actors, and the end customer. Together, they provide a comprehensive view of how the delivery process was intended to function.

6.2.1 AS-IS Smart Strategy Board

The selected project is aimed at delivering over 100 MW of fast-ramping capacity to support grid stability and renewable integration. This aligns with the case company's broader strategy of enabling the energy transition through flexible, modular power solutions (Case Company, 2025a). Figure 6.1 presents the AS-IS SSB used to capture these elements.

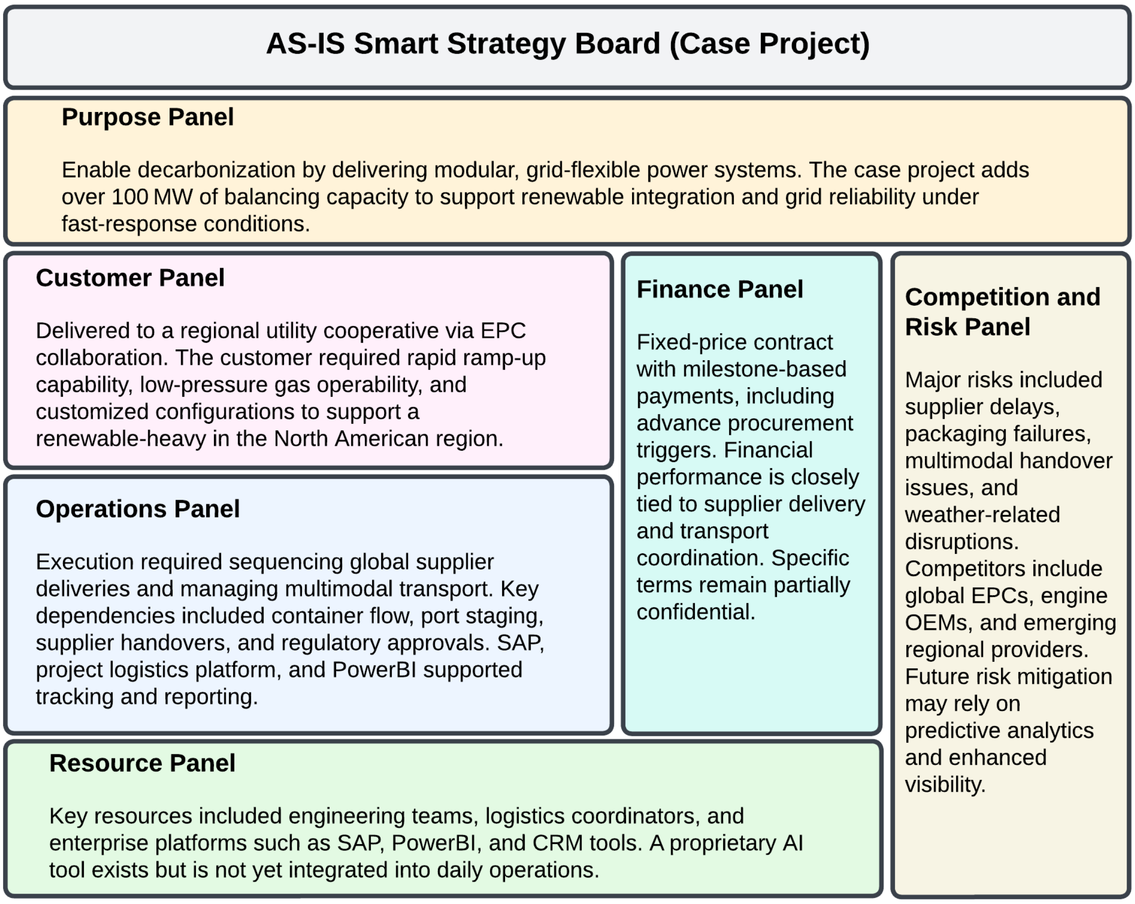

Figure 6.1. AS-IS Smart Strategy Board for the Case Project.

The end customer is a utility based in North America. The delivery is managed through an EPC contractor, with additional oversight from regulators and local grid authorities. The equipment needs to meet low-pressure operability and fast-start performance targets, with coordination managed across multiple stakeholders (Client Utility, 2023).

The project follows a fixed-price model with milestone-based payments. Procurement and delivery progress trigger invoicing events. While supplier performance influences internal timelines, no formal metrics are tied directly to financial release.

Key risks include delayed confirmations and incomplete documentation. These issues often contribute to transport disruptions. Global instability, ranging from container bottlenecks to shifting permit rules, adds further complexity. These risks are managed reactively through informal communication and manual oversight.

Execution relies on multiple systems. SAP is used for purchase orders and invoicing. The project logistics platform tracks shipping progress. PowerBI supports internal reporting. In practice, coordination occurs largely through Excel and email, with data manually transferred between tools.

Resources are allocated across project management, procurement, logistics, and engineering teams. Each team uses separate systems and routines to manage their part of the delivery process. While limited AI capabilities exist within the company—primarily for tasks like text refinement—they are not deployed in this specific project.

The next section continues this framing by translating strategic intent into the project's delivery logic using the BMC.

6.2.2 AS-IS Business Model Canvas

The BMC is a visual tool that describes how an organization creates, delivers, and captures value. Although originally developed for firm-level strategy, the BMC can be adapted to complex project environments to clarify how stakeholders, activities, and resources align around a specific value proposition (Osterwalder et al., 2010). In this project, the BMC supports a shift from strategic framing to operational structure. It outlines how the delivery process is structured and what roles are involved in coordinating value to the end customer. Figure 6.2 presents the AS-IS BMC used for this purpose.

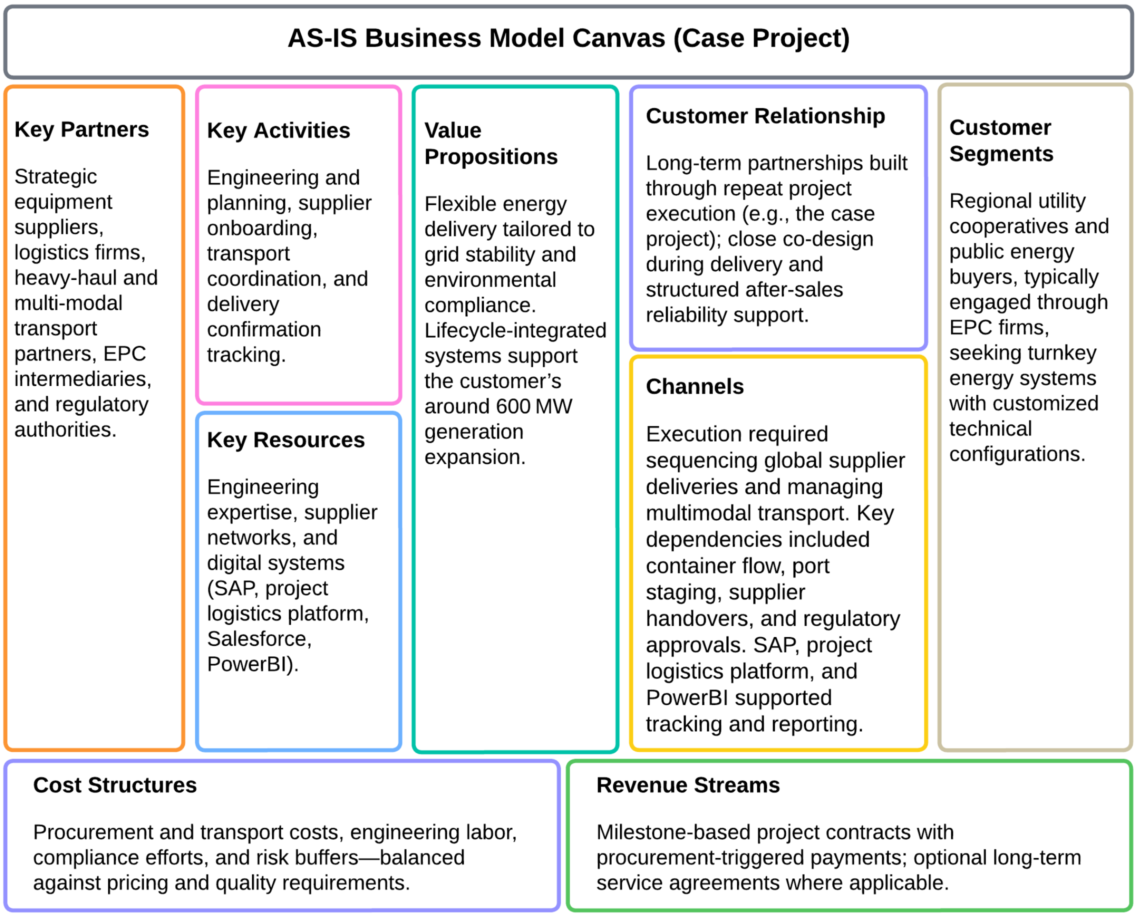

Figure 6.2. AS-IS Business Model Canvas for the Case Project.

The utility operates in a North American market. The delivery is handled through an EPC intermediary, which acts as the contractual partner and coordination bridge. While the utility sets technical expectations, day-to-day communication occurs primarily with the EPC. Customer requirements focus on rapid deployment, grid flexibility, and compliance with site-specific regulations (Client Utility, 2023).

The project aims to provide over 100 MW of balancing capacity through modular, fast-ramping engine units. The solution is positioned as a means to support renewable energy integration and ensure grid stability. Although life-cycle support is referenced during project planning, it is not always formally included in the scope (Case Company, 2023).

Sales are conducted through Request for Quotation (RFQ) processes initiated by the EPC. Follow-up activities occur through email, meetings, and platforms like Salesforce. While PowerBI is used for reporting, integration between these tools and procurement coordination remains limited.

The core activities include procurement planning, logistics scheduling, and documentation handling. No new suppliers are onboarded for this project. The focus is on managing execution across known partners under tight delivery windows.

Key partners include global equipment suppliers, transport providers, EPC actors, and local port and customs agents. Coordination relies heavily on supplier performance, particularly in readiness, packaging quality, and documentation accuracy.

Costs are driven by procurement value, freight charges, risk buffers, and regulatory compliance. Procurement teams aim to manage supplier pricing while balancing quality, documentation, and schedule risks.

Revenue is generated through a fixed-price project contract with milestone-triggered invoicing. Advance payments are required to initiate procurement activities. No formal delivery reliability metrics are linked to payment conditions.

While the BMC outlines how the project's delivery is structured, it does not reflect how well these components perform in practice. The following section transitions from structural framing to process-level analysis through the development of the AS-IS Value Stream Map.

6.3 Construction of the AS-IS Value Stream Map

This section constructs the AS-IS Value Stream Map to visualize how supplier deliveries were coordinated in the case project. Rather than focusing only on delivery outcomes, the map highlights the operational flow behind those outcomes. It captures step-by-step coordination across teams and systems. The map is built using structured data and interview insights, forming the analytical foundation for diagnosing reliability issues.

6.3.1 Mapping Process

The AS-IS Value Stream Map was developed to visualize how supplier delivery coordination is structured in practice. Rather than focusing solely on delivery metrics, the map highlights coordination mechanisms, such as supplier engagement and process handovers, that influence reliability. This supports the research objective of analyzing delivery reliability through the lens of process coordination.

The structure of the map was informed by internal documentation, SAP outputs, and interviews with key stakeholders. A joint interview on March 20 included the strategic purchaser, logistics coordinator, and transport manager. Follow-up sessions with the strategic purchaser on April 2 and April 23 clarified specific responsibilities, system interactions, and step-level accuracy.

The map was initially drafted using EdrawMax and then refined in Lucidchart. This allowed layering of diagnostic features and grouping of failure points. To improve clarity, the Value Stream Map is first presented in a structured tabular format before being shown as a visual diagram in Section 6.3.4.

The first table (Table 6.1) outlines the eight core steps in the supplier delivery process. Each step is linked to a responsible actor and the system used. The second table (Table 6.2) builds on this structure by identifying process weaknesses. It also presents eight validated performance metrics, including measures of delivery deviation, compliance, and supplier consistency (see Appendix 1). Each step is also evaluated for its potential suitability for AI-supported improvement. The next subsection explains the process logic and graphical elements used in the visual AS-IS Value Stream Map.

Table 6.1. AS-IS VSM Structure – Part 1.

Step No.	Step Name	Process Description	Primary Actor(s)	System Used	Known Bottlenecks
1	Project Procurement Kickoff	Internal alignment and initial PO prep; naming and coding of materials	Project Controller + Project Team	SAP, Excel (unstructured)	No standard naming in PO; hard to trace materials
2	Quotation Request to Supplier	RFQs are sent to suppliers and followed up manually; responses vary in speed and quality	Project Team	SAP, Email	No tracking of quote response timing; manual follow-up cycles
3	PO Release and Supplier Confirmation	POs are released and awaiting supplier confirmation; delays in response common	Procurement + Supplier	SAP, Email	Confirmation not always tracked; delayed or missing supplier replies
4	Supplier Manufacturing and Packing	Supplier manufactures components and prepares for dispatch; packing readiness varies	Supplier + 3PL Packing Partner	Supplier systems, email, Excel	Readiness not tracked; packing often unclear until asked
5	Readiness Check and Dispatch Coordination	Logistics checks if items are ready for shipment; plans dispatch and books transport	Logistics Coordinator + Transport Manager	SAP, Email, Excel	Packing status unclear; frequent shipment rollovers; poor readiness visibility
6	Outbound Dispatch and Port Delivery	Packed goods are dispatched toward port; transport booked and initiated	Logistics / Transport	Project logistics platform	Staging time gaps
7	Port Buffering and Container Handover	Goods arrive at port and wait for shipment; containers staged or held in buffer	3PL/Port + Transport	Project logistics platform, SAP (minor)	Long wait time; port rollover risk; poor visibility on buffer timing
8	Final Delivery and Site Staging	Final goods delivered to site and staged; defects or complaints raised if issues found	Transport / Site Team	Project logistics platform, Email, Excel	Damaged or mismatched goods; no structured complaint tracking

Table 6.2. AS-IS VSM Structure – Part 2.

Step No.	Step Name	Delay / Waste Type	Available Data	Potential AI Model(s)	Target Performance Metric(s)
1	Project Procurement Kickoff	Overprocessing, Waiting, Miscommunication	Partial — PO date in SAP; naming issue via interview	-	Procurement Lead Time (PLT)
2	Quotation Request to Supplier	Waiting, Overprocessing, Information Waste	Partial – RFQ date in SAP; quote receipt not logged	FIS (if informal evaluation of quote completeness); otherwise None	Procurement Lead Time (PLT) — quoting delays increase total PLT
3	PO Release and Supplier Confirmation	Waiting, Information Waste, Overprocessing	Partial — PO release date in SAP; confirmation not tracked	LightGBM	Procurement Lead Time (PLT)
4	Supplier Manufacturing and Packing	Waiting, Information Waste, Defects	Limited — readiness shared manually; no system timestamp	LightGBM, FIS	Value-Added Time (VAT), Procurement Lead Time (PLT), Defect Ratio, Raw Delivery Deviation (RDD)
5	Readiness Check and Dispatch Coordination	Waiting, Overprocessing, Defects	Partial — dispatch dates available; readiness manually tracked	FIS, LightGBM	Value-Added Time (VAT), Delay, Delivery Reliability (DR%)
6	Outbound Dispatch and Port Delivery	Waiting, Transport Waste, Defects	Yes — ETS and ATS in the project logistics platform; delay measurable	LightGBM	Delay, Delivery Reliability (DR%), Delivery Window Compliance Rate (DWCR)
7	Port Buffering and Container Handover	Waiting, Inventory Waste, Transport Waste	Yes — ETS/ATS in the project logistics platform; buffer timing traceable	LightGBM, ANN	Delay, Delivery Reliability (DR%)
8	Final Delivery and Site Staging	Defects, Overprocessing, Waiting	Partial — delivery in the project logistics platform; complaints in Excel/interviews	Clustering (K-means), DBSCAN	Defect Ratio (%), Delivery Reliability (DR%), Deviation Variability (DV%)

6.3.2 How to Read the VSM Diagram

To support interpretation of the AS-IS Value Stream Map, this section introduces the symbols used to represent coordination steps, material flows, risk zones, and performance indicators. All visual notation follows standardized conventions based on Lucidchart's VSM guide (Lucidchart, 2025).

Each process step is shown as a labeled rectangle containing the responsible actor(s) and the associated activity. These steps are ordered sequentially to reflect how supplier deliveries were coordinated from project kickoff through final handover.

Thin arrows indicate information flow between steps. In this case, they represent exchanges through SAP, Excel trackers, Outlook email chains, and other semi-manual coordination tools. This visualizes the fragmented but traceable nature of early-stage communication.

Thick arrows represent material flow—used only in steps where physical goods are moved. These include shipment dispatch, port transfer, and site delivery. The switch from thin to thick arrows highlights where the flow shifts from digital coordination to physical execution.

Kaizen burst symbols are placed under each process step to indicate known inefficiencies or improvement opportunities. These symbols were included based on interview confirmations and performance data. For example, delays in confirmation or repacking errors were explicitly validated and are marked accordingly.

Inventory triangle symbols are placed between key process steps to indicate virtual buffers in the case company's flow. These appear between manufacturing, dispatch, port transfer, and final staging—highlighting where containers are temporarily held in the absence of traditional warehousing. While they do not explicitly signal risk, their placement reflects points where inventory is used to absorb coordination gaps that may otherwise disrupt flow.

A summary panel on the right side of the map aggregates the eight performance metrics calculated for this analysis. This panel provides a consolidated view of delivery reliability, delay, defect ratio, and other measures, while keeping the main flow visually uncluttered.

Together, these visual elements are used to construct a readable, coordination-focused representation of the AS-IS supplier delivery flow. The next section defines and explains each performance metric in detail.

6.3.3 Metrics and Measurement Logic

To quantify delivery performance across the AS-IS process, eight metrics were calculated based on SAP data, internal documents, and stakeholder interviews. These metrics were selected to reflect key aspects of supplier coordination and reliability, and they serve as objective indicators of performance across the mapped delivery flow.

The metrics are not isolated indicators—they reflect how coordination outcomes accumulate across steps. While delivery reliability can be defined conceptually, these measurements make the concept traceable and comparable. Each metric targets a specific coordination point or failure pattern identified in the process analysis.

The selected metrics include Delivery Reliability (DR), Procurement Lead Time (PLT), and Delivery Delay, which capture overall timeliness and process speed. Value-Added Time (VAT) and Defect Ratio reflect process efficiency and quality outcomes. Raw Delivery Deviation (RDD), Delivery Window Compliance Rate (DWCR), and Deviation Variability (DV) provide a more granular view of timing consistency and supplier-specific variation.

The calculation logic aligns with the case company's official delivery definitions, particularly around International Commercial Term (Incoterm)-driven data selection. For example, Free Carrier (FCA) deliveries use the Confirmed Delivery Date, while Delivered at Place (DAP) and Delivered Duty Paid (DDP) deliveries rely on the Goods Receipt (GR) Date. Statistical delivery dates were used as a common benchmark to identify both early and late deviations. These logic rules, source fields, and applied formulas are documented in full in Appendix 1.

Table 6.3. Summary of Calculated Delivery Performance Metrics.

Metric	**Definition**	**Unit**	**Result**	**Associated Step(s)**
Delivery Reliability (DR)	Deliveries arriving within a 2-day grace period after planned delivery date	%	73.38%	Step 4, Step 6
Procurement Lead Time (PLT)	Days from PO creation to supplier readiness or goods receipt, depending on Incoterm	Days	91.54	Step 3
Delivery Delay	Late days beyond the planned delivery date (only late deliveries considered)	Days	46.94	Step 6
Value-Added Time (VAT)	Time from supplier readiness to goods receipt	Days	23.58	Step 6
Defect Ratio	Share of deliveries triggering QE/QV/XF notifications	%	13.39%	Step 8
Raw Delivery Deviation (RDD)	Absolute difference between planned and actual delivery date (± values)	Days	5.00	Step 4, Step 6
Delivery Window Compliance Rate (DWCR)	Percentage of deliveries within -1 to +2 day window of planned date	%	83%	Step 6

Continued on next page

Table 6.3 – continued from previous page

Metric	Definition	Unit	Result	Associated Step(s)
Deviation Variability (DV)	Standard deviation of delivery deviation per supplier	Days	24.45	Step 8

Table 6.3 presents an overview of all eight metrics, including their definitions, units of measurement, results, and the process steps they are most closely associated with. Together, these values provide a grounded baseline for interpreting coordination performance, setting the stage for the diagnostic findings presented in Section 6.4.

6.3.4 AS-IS VSM Diagram

The AS-IS Value Stream Map brings together the structure, actors, systems, performance metrics, and known weaknesses of the current delivery process into a single visual overview. It complements the previous tables by enabling a more intuitive reading of where coordination issues occur across steps and systems.

The diagram uses standard VSM notation as introduced earlier and follows the same eight-step flow presented in the structured tables. Each step is annotated with system usage, process ownership, and improvement markers. Performance metrics are summarized on the right to link process flow with delivery outcomes.

This visual anchor supports the diagnostic analysis that follows, where performance patterns and coordination gaps are examined more closely. Figure 6.3 presents the AS-IS Value Stream Map developed for the case project.

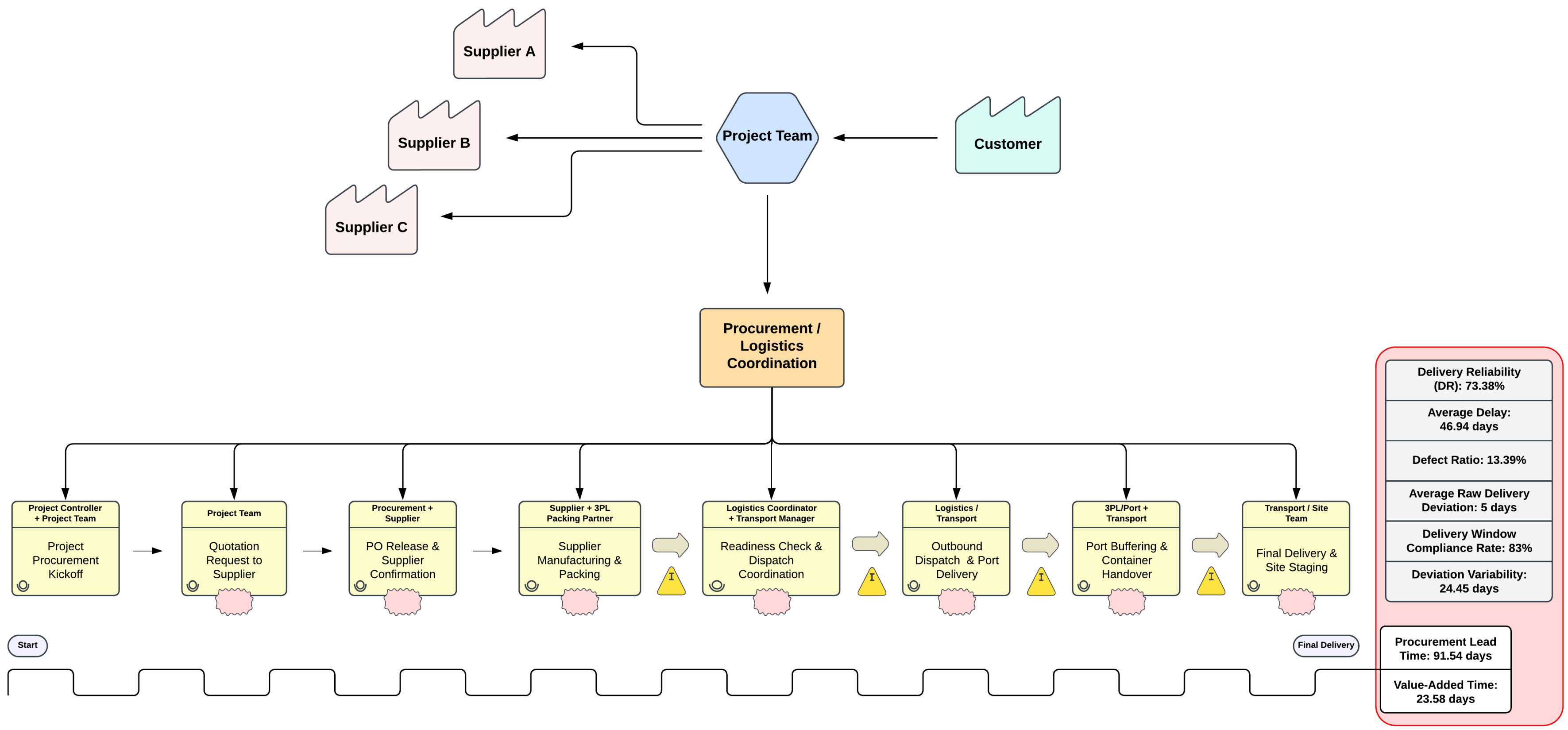

Figure 6.3. AS-IS Value Stream Map of the Case Project.

6.4 Diagnosis of the Current State

This section analyzes the current delivery flow using both metric results and process observations. It identifies where coordination failures occur, how they affect performance, and why they persist. The diagnosis combines quantitative findings with validated practitioner insights to expose the root causes of delivery variability.

6.4.1 Metric Findings

The eight calculated performance metrics reveal consistent coordination challenges across the supplier delivery flow. DR stands at 73.38%, indicating that more than one in four deliveries miss the targeted window. When delays occur, they are substantial—averaging 46.94 days—highlighting the lack of anticipation, especially during readiness and dispatch.

PLT averages 91.54 days, suggesting prolonged cycles between PO creation and readiness. This is driven in part by delayed supplier responses and manual coordination effort. VAT accounts for only 23.58 days, meaning most of the total lead time consists of waiting, idle handovers, or rework.

Post-delivery feedback is not systematically recorded. Still, the Defect Ratio of 13.39% indicates that more than one in ten shipments trigger formal issue notifications. While this reflects quality concerns, it also points to communication breakdowns between the site team and the supply chain function.

The final three metrics add further clarity. RDD, at an average of 5.00 days, shows that even seemingly “on-time” deliveries fluctuate noticeably. DWCR is moderate at 83%, meaning 17% of deliveries fall outside the tight -1 to +2 day window. DV averaged 24.45 days but differed significantly by supplier, confirming inconsistent behavior across vendors and reinforcing the need for segmented management strategies.

Together, these findings confirm that delivery reliability is not simply a matter of timeliness—it is the outcome of layered coordination gaps and fragmented ownership across the process.

6.4.2 VSM Weaknesses and Validation

Beyond the quantitative findings, the AS-IS Value Stream Map highlights structural weaknesses that contribute to delivery variability. These weaknesses were confirmed in a joint interview with the strategic purchaser, transport manager, and logistics coordinator, then reinforced in later follow-ups with the strategic purchaser.

Early-stage coordination suffers from missing or late quotations, unclear communication between sales and procurement, and non-standardized PO creation. Steps 2 and 3 rely heavily on email and Excel tracking, with no structured confirmation field in SAP. This results in coordination delays and communication breakdowns between internal teams and suppliers. These patterns are common in supply chains with limited digitalization (Sakala & Bwalya, 2023).

Steps 5 and 6 exhibit high variability caused by last-minute planning and unreliable readiness updates. Similar issues were observed during actual engine arrivals in the case project (Client Utility, 2024). Tracking in the project logistics platform is disconnected from SAP updates, and shipment documents are not always synchronized. Readiness validation often occurs reactively, and transport is confirmed based on best-effort communication rather than data flow. This reflects a lack of upstream visibility that can distort the entire coordination flow (Jones & Womack, 2002).

In Step 8, final delivery feedback and defect reporting remain loosely coordinated. Site-level issues are recorded in a mobile application, but not directly linked to SAP or upstream procurement records. This prevents systematic learning and hides recurring quality or packaging issues in project closure. Similar visibility gaps at late stages are a known risk factor in global project logistics (Basu, 2023).

Throughout the process, roles are functionally split—procurement owns equipment readiness, logistics owns dispatch, and the site team owns receipt—yet handovers are informal. Coordination depends on individual vigilance and undocumented workarounds. This fragmentation contributes directly to delivery risk, as confirmed across three interviews. Practitioners emphasized that planning gaps and confirmation delays are common. Poor traceability was described as a routine part of project execution. These insights validate that observed inefficiencies in the Value Stream Map are not hypothetical. They reflect systemic gaps in accountability and interdepartmental coordination.

6.4.3 Summary of What's Broken

The findings from both metrics and map interpretation reveal three critical failure zones that consistently undermine supplier delivery reliability in the case project:

1. Supplier confirmation and follow-up: Quotation handling and PO confirmations in Steps 2–3 suffer from slow execution and inconsistent tracking practices. The lack of formal data fields for supplier confirmations forces repeated email follow-ups and contributes to long procurement lead times.

2. Shipment readiness and dispatch: In Steps 5–6, readiness updates are unreliable and often unvalidated. Transport bookings occur reactively, based on vague estimates rather than system-driven timelines. Disconnects between SAP and project logistics platform prevent accurate status visibility.

3. Post-delivery feedback and supplier tracking: Final delivery quality and defect tracking (Step 8) are fragmented. Mobile apps are used at the site, but findings are not looped back into the Enterprise Resource Planning (ERP) or used to evaluate supplier performance. Repeated issues remain hidden from upstream actors. These tracking failures create delivery uncertainty and raise the risk of milestone disruption, especially in time-sensitive projects (Vanhoucke, 2013).

Each zone reflects structural miscoordination and fragmented information flow. The AS-IS process does not lack resources—it lacks connected visibility and structured accountability. These gaps show that improvement requires targeted interventions—not wholesale redesign. The next chapter explores how AI models can be integrated into the TO-BE process to reinforce these weak points without adding system complexity or removing human judgment.

Chapter 7

Value Stream Redesign for Delivery Reliability

This chapter presents the redesigned supplier coordination process for the case project. It addresses specific delivery issues mapped in Chapter 6 by introducing Artificial Intelligence (AI) decision-support at key friction points. Instead of changing the entire flow, the TO-BE design reinforces three critical coordination zones using lightweight, well-matched AI tools. Each model, LightGBM, Fuzzy Inference System (FIS), and Clustering, is placed where human judgment struggles and visibility is low. These models reshape day-to-day decisions, align with existing data and tools, and create a shift from reactive follow-ups to proactive control. Strategic framing tools and a phased roll-out strategy ensure the redesign is not just conceptually strong, but also practical and scalable in real project environments.

7.1 From Diagnosis to Redesign

This chapter builds directly on the analysis presented in Chapter 6. The TO-BE design responds to the practical coordination issues observed in the case project. These were not hypothetical inefficiencies. They were confirmed through data analysis and stakeholder validation.

The AS-IS Value Stream Map revealed specific failure points. Supplier confirmations arrived late. Shipment readiness was unclear. Dispatches were often reactive. Each breakdown added delay and uncertainty to the delivery flow. These problems were not caused by a lack of tools, but by the absence of structure at key decision points.

Rather than overhaul the process, this redesign targets the weak spots. The eight-step flow remains intact. No functions are removed. Instead, decision-support is added where visibility is missing and manual work dominates. As emphasized in recent lean manufacturing literature, improvement begins where waste accumulates, and process redesign should target the points of highest inefficiency (Ghelani, 2021).

This logic also follows the core principle of Value Stream Mapping (VSM): redesign should focus on stages where value is lost or coordination breaks down (MacCarthy et al., 2022). As Chapter 6 showed, these breaks occur in three zones—early supplier engagement, shipment planning, and post-delivery tracking. The TO-BE model introduces support only at these points.

AI is not added for its own sake. Each model serves a defined role. It supports proactive insight and post-project analysis. The aim is not automation. It is foresight. The next section explains the model selection and how each fits into the redesigned flow.

7.2 AI Design Basis for TO-BE Process

This section explains why each AI model was selected and where it fits into the redesigned coordination flow. The models are not added for novelty—they solve real coordination problems observed in the AS-IS analysis. Each one is matched to a step with limited oversight and high decision uncertainty. Instead of replacing existing systems, the models work alongside current tools to provide predictive support exactly where it is needed.

7.2.1 Model Placement and Coordination Fit

The TO-BE redesign introduces three artificial intelligence models, each placed at a specific coordination point where the AS-IS process showed persistent breakdowns. These placements were not hypothetical. They were derived directly from performance analysis and stakeholder interviews, where recurring delays and fragmented decision-making were consistently highlighted.

The placement logic follows a simple structure. Each model is matched to a process step that lacks visibility or requires structured decision support. LightGBM is introduced in Step 4, where supplier confirmations often fail to predict later delays. This placement targets the gap between confirmation and readiness, where teams currently rely on subjective updates. In Steps 5 and 6, a FIS model is used to evaluate shipment readiness based on partial packaging and documentation signals. These steps were identified in Chapter 6 as prone to reactive planning and unclear dispatch decisions. Finally, Step 8 uses Clustering to structure post-delivery data into actionable supplier profiles. This step addresses the lack of formal learning from past performance.

Each placement is supported by structured data already collected in the case company, including procurement and shipment status indicators. Stakeholders confirmed the placements match operational pain points and can be introduced without altering existing systems.

Table 7.1. Mapping of AI Models to Supplier Coordination Gaps in the TO-BE Process.

Process Step	Identified Problem	Model Applied	Target Metric(s)	Data Source(s)
Step 4 – Supplier Monitoring	Limited visibility after PO confirmation	LightGBM	Delay, Delivery Reliability, Lead Time Deviation	Datasets B, D
Steps 5–6 – Readiness Check	Manual shipment readiness checks	FIS	Readiness Score, Dispatch Timeliness	Dataset D
Step 8 – Supplier Evaluation	No structured feedback loop	Clustering	Delay Variability, DR%, Defect Ratio	Datasets B, C

As shown in Table 7.1, each model is introduced as a lightweight overlay on top of the existing process flow. No changes are made to process ownership or task sequence. The redesign simply inserts predictive checkpoints at the moments where coordination most often breaks down. The following section explains how these model placements align with the performance metrics already used in the case company.

7.2.2 KPI Justification and Data Compatibility

Each model introduced in the TO-BE design is not only functionally aligned with a coordination challenge, but also justified by the performance metrics already available in the case company. This alignment ensures that model selection is grounded in operational reality, not speculative design. The purpose of this subsection is to show that the proposed models are compatible with existing datasets and are capable of producing traceable improvements in process oversight.

LightGBM is introduced to forecast supplier-related delivery delays after PO confirmation. This model is suited to structured, tabular data and is commonly used in delivery deviation classification tasks. Its application is justified by the availability of target variables such as delivery reliability, delay duration, and planned versus actual lead times. These indicators are stored in Datasets B and D, which include SAP-confirmed delivery records and manually logged tracking sheets. The model also benefits from categorical features such as Incoterm, supplier ID, and equipment type, which help improve classification performance without requiring extensive feature engineering. This makes LightGBM a strong fit for early-stage risk filtering in project supply environments.

The FIS applied in Steps 5 and 6 relies on semi-structured or qualitative inputs, including packaging weight, loading status, and shipment readiness fields. These inputs are available in Dataset D, which contains manually compiled dispatch records. Interviews confirmed that these readiness indicators are already used informally by logistics teams to assess whether a shipment is complete. FIS formalizes this judgment by translating vague or partial information into rule-based readiness scores. Because it does not require labeled training data, and because it is interpretable by non-technical users, the model is particularly well suited to processes where system maturity is low but coordination complexity is high.

Clustering is applied in Step 8 to group suppliers based on behavioral trends observed after delivery. Unlike supervised models, Clustering does not require pre-labeled outputs. Instead, it relies on delivery metrics such as average delay, reliability rate, defect ratio, and delivery window compliance. These can be calculated from existing data in Datasets B and C, making the model usable without new data collection. The model generates segment profiles that help distinguish consistently delayed suppliers from those with more stable performance. These outputs support prioritization and escalation strategies that are currently handled reactively or based on anecdotal evidence.

This alignment with available Key Performance Indicators (KPIs) confirms that each model builds on existing operational logic. The next section explains how these models can be integrated into daily workflows.

7.2.3 Integration Within Coordination Processes

While model selection is driven by process needs and data availability, successful adoption depends on how well each tool fits the existing workflow. In the case company, system maturity is mixed. Core delivery data is captured in SAP and Excel trackers, but coordination often relies on manual inputs and email-based routines. This context calls for simple, transparent models that align with existing tools.

LightGBM is well suited to this environment. It can be deployed as a local Python script or integrated into an Excel or PowerBI dashboard (Microsoft Corporation, 2025). The model requires input features already available in exported SAP reports—such as PO date, supplier ID, equipment class, and lead time deviation—and can be run periodically to flag high-risk orders. Outputs such as risk scores or binary delay warnings can be visualized directly within familiar follow-up sheets, using conditional formatting or color-coded alerts. This structure allows users to retain ownership of decisions while benefiting from a predictive warning layer.

The FIS for shipment readiness is similarly easy to implement. Its logic can be built in Excel using rule-based formulas or simulated in MATLAB using fuzzy logic editors (The Mathworks, Inc., 2025a). In either case, the system translates operational signals—such as missing packing weights or late documentation entries—into a readiness score that helps logistics teams decide whether a shipment is suitable for dispatch. For this purpose, a Mamdani-type system is recommended. It allows expert-driven rules to be translated into interpretable outputs—ideal for low-automation contexts where human oversight remains critical (The Mathworks, Inc., 2025b).

Clustering is applied retrospectively, making it even easier to deploy (Palit, 2025). It can be executed in Python or R using supplier delivery records from Datasets B and C. These records are already used in quarterly reporting and can be extended to support segmentation dashboards. Supplier groups can be visualized in PowerBI or Excel, showing which suppliers are chronically late, defect-prone, or inconsistent. This information feeds directly into planning and review cycles without requiring real-time updates. Table 7.2 summarizes where each model is deployed, what data it uses, and which role consumes the output—highlighting their practical alignment with existing coordination routines.

Table 7.2. AI model deployment context—data inputs, process steps, and role alignment.

Model	**Primary Data Source**	**Process Step**	**User / Output Consumer**
LightGBM	SAP PO exports, Excel delivery logs	Step 4: Supplier confirmation	Strategic purchaser
FIS (Mamdani)	Excel dispatch trackers, manual packaging data	Steps 5–6: Shipment readiness check	Logistics coordinator
Clustering	SAP delivery records, defect logs	Step 8: Post-delivery follow-up	Strategic purchaser, transport manager

Each model integrates into the company's reporting stack, Excel, PowerBI, and SAP exports, without requiring new platforms or system integration. The deployment mirrors current workflows, using file-based inputs and visual outputs already familiar to procurement and logistics. This makes the TO-BE design feasible and actionable. It is also scalable in a project-driven environment where flexibility and interpretability matter as much as technical performance.

7.3 Projected Improvement Impact

The TO-BE Value Stream Map integrates three AI-supported interventions—targeting delivery delays, shipment uncertainty, and unstructured supplier follow-up—based on coordination breakdowns identified in the AS-IS process. Although not yet implemented in a live setting, the redesigned process is supported by literature-backed model behavior, case-specific process logic, and simulation where applicable. The following analysis outlines each model's projected operational impact and expected performance improvements.

Before diving into each model's projected impact, Table 7.3 offers a consolidated view of how each intervention addresses a specific coordination failure and what operational value it brings.

Table 7.3. Overview of AI model interventions, coordination targets, and expected operational impact.

Model	**Targeted Coordination Breakdown**	**Expected Operational Impact**
LightGBM	Unreliable supplier confirmations and lack of early risk signals (Step 4)	Enables proactive follow-up by ranking suppliers based on delay risk; reduces last-minute escalations
FIS (Mamdani)	Informal and inconsistent shipment readiness checks (Steps 5–6)	Adds structured decision support using partial shipment data; prevents premature dispatches and container rollovers
Clustering	No structured learning from post-delivery data (Step 8)	Segments suppliers by reliability and behavior; supports smarter prioritization and escalation in future projects

The following subsections draw on peer-reviewed studies where each AI model was applied in comparable supply contexts. These findings are used to support the projected improvements in both project coordination and daily operational work.

7.3.1 LightGBM – Delay Risk Prediction

LightGBM is introduced in Step 4 to predict supplier delays shortly after PO confirmation. This placement addresses a critical blind spot identified in the AS-IS process, where DR stood at 73.38% and average delays reached 46.94 days. Confirmation updates were reactive and rarely triggered early escalation. LightGBM transforms this by generating risk flags based on historical delivery patterns, confirmation speed, supplier category, and Incoterm type.

In related applications, Sani et al. (2023) applied a Bayesian-optimized LightGBM model to flag high-risk deliveries using structured procurement data. The model performed well even under class imbalance and produced actionable alerts without full system integration. A two-stage LightGBM pipeline was implemented to classify delays and estimate lead time deviations, as shown in the work by Wozniak et al. (2024). Their results showed the model's strength in logistics environments with incomplete visibility.

Pasupuleti et al. (2024) reported four key gains using gradient-boosted models in multi-modal supply chains. These included a 12% improvement in lead time efficiency, a 15% increase in forecasting accuracy, a 10% reduction in overstock and stock-outs, and 95% accuracy in fulfillment prediction. Wang et al. (2024) further demonstrated that a LightGBM model trained for back-order detection achieved 100% accuracy, even in highly imbalanced procurement data.

While these results are not directly transferable, they confirm the model's robustness for coordination forecasting. In the case project, LightGBM supports early risk visibility at Step 4. It enables proactive follow-up and reduces delays before they spread downstream.

For the case company, the operational impact of LightGBM is most visible in how it changes the role of the strategic purchaser. Currently, follow-ups are triggered by subjective urgency or milestone proximity. With the model in place, purchasers can access a prioritized risk list derived from historical behavior. This makes it easier to identify suppliers that need early intervention and avoid those likely to perform reliably. As Raymond and Bergeron (2008) note, project success depends not only on technical tools but on timely, low-friction access to relevant information. By embedding LightGBM outputs into existing Excel or PowerBI sheets, the case company can shift from reactive troubleshooting to proactive control—without disrupting current routines.

7.3.2 Fuzzy Inference System – Shipment Readiness Filtering

FIS is applied across Steps 5 and 6 to evaluate shipment readiness before dispatch. In the AS-IS process, readiness decisions relied on informal communication and unstructured judgment. This led to disrupted dispatch flow and avoidable transport complications. Interviews confirmed frequent gaps in packaging data and shipment documentation.

The FIS model uses expert-defined rules to score shipment readiness. Input signals include missing packaging data, low VAT values, unchecked loads, and flagged material statuses. To validate this design, Dataset D was used to simulate coordination risks. Over 5000 shipment records were filtered using structured logic. Three scenarios were tested: (1) missing packaging weight, (2) unchecked load confirmation, and (3) cases flagged for unused material status (See Appendix 2). These mapped directly to logic rules defined in the FIS framework.

The simulation results are summarized in Table 7.4. A total of 5815 rows matched the incomplete packaging condition. Another 4824 cases showed undocumented readiness. No cases triggered the repack or rollback rule. These findings confirm that the FIS logic targets high-frequency coordination failures without false positives.

Table 7.4. Data-Supported Simulation of Coordination Improvement via FIS Readiness Filtering (Steps 5–6).

AS-IS Bottleneck Scenario	**Observed Frequency**	**FIS Rule Outcome**	**Projected Impact**
Incomplete packaging prior to dispatch	5815 cases	FIS flags "not ready" based on missing fields	Blockage prevented
Dispatch readiness undocumented (both fields missing)	4824 cases	Readiness = LOW → blocked release	Risk avoided
Dispatch repacked or rolled back	0 cases	No trigger observed	Not applicable

This approach is supported by applied studies. Berbiche et al. (2024), Sazvar et al. (2022), and Liu and Yang (2020) demonstrate how FIS models improve shipment control and lead time in complex logistics. Noueihed (2022) applied fuzzy rules to unstable supply systems with limited data. Shenoi et al. (2021) used fuzzy cognitive modeling to identify mitigation points in manual-intensive chains. These works confirm that rule-based coordination tools offer strong impact in low-automation environments.

In daily operations, this intervention helps the logistics coordinator act early. Today, readiness checks often rely on memory or informal chats. The FIS acts as a structured “GO/NO-GO” gate before booking transport. It improves dispatch readiness and stabilizes delivery scheduling. This reflects the principle of anticipatory resilience, as defined by Munir et al. (2022)—the ability to detect early risk signals and prepare before failure occurs.

7.3.3 Clustering – Post-Delivery Supplier Segmentation

Clustering is introduced in Step 8 to address a persistent gap in the AS-IS process: the lack of structured feedback after delivery. Although the company collects delay and defect data, it does not use this information to improve future coordination. All suppliers are tracked uniformly, even though their reliability and responsiveness vary widely.

In the TO-BE model, K-means Clustering is applied to delivery metrics such as average delay, DR, defect ratio, and DWCR. These inputs are already present in Datasets B and C. The goal is to segment suppliers into behavior-based groups. This allows teams to shift from general tracking to targeted follow-up, making coordination more focused and enabling earlier containment of recurring issues.

This change is expected to reduce effort waste and cut down last-minute escalations. Suppliers that frequently cause disruptions can be separated from those who perform reliably. That separation supports better planning and helps teams respond before small issues grow. These projected benefits are supported in applied studies. Rezki and Mansouri (2024) found that clustering improved early risk detection in supplier coordination. Ul Husna et al. (2024) showed that K-means helped clarify decision pathways in large public procurement. Tiwari et al. (2023) reported improved transport planning and lower routing overhead. Lahtinen (2021) demonstrated that clustering enabled fast supplier classification in operational settings.

Clustering is not a predictive tool. It does not estimate future values but highlights structural patterns in behavior. This adds a decision layer that helps teams intervene earlier and focus attention where it is most needed.

In daily operations, the strategic purchaser can flag vendors that repeatedly miss timelines or deliver poor documentation. The transport manager gains visibility into where issues start. Instead of spreading attention evenly, resources can be aligned with risk and variability. Clustering turns delivery follow-up into a coordination tool. It supports better planning and faster response without changing the underlying systems.

Together, these changes show that the TO-BE Value Stream Map is more than a technical redesign. It introduces a new coordination logic. The next section builds on this logic using the Smart Strategy Board (SSB) and Business Model Canvas (BMC).

7.4 Strategic Framing of the TO-BE Process

This section presents the strategic foundation of the TO-BE design by reframing how supplier coordination, value delivery, and process ownership are structured in the redesigned project model. Building on the AS-IS analysis in Chapter 6, it introduces two tools—the TO-BE SSB and BMC. These tools visualize how data-driven control and structured supplier engagement are embedded into the future-state coordination flow. Collectively, these tools provide a high-level view of how the case project's delivery model evolves from milestone-driven oversight to signal-based execution, establishing the framework upon which the redesigned Value Stream Map is built.

7.4.1 TO-BE Smart Strategy Board

The AS-IS SSB presented in Chapter 6 revealed a reactive coordination structure. Decision-making relied on milestone triggers, manual updates, and loosely defined ownership across procurement, logistics, and transport. Coordination was distributed but not aligned, and strategic risks—such as delivery delays and readiness mismatches—were managed only after they became visible. These weaknesses reflected a fragmented flow logic and the absence of predictive control.

The TO-BE SSB addresses these limitations by embedding predictive checkpoints and role-specific accountability into the core coordination structure. Rather than waiting for issues to surface, the redesigned model introduces three decision-support mechanisms aligned with key breakdown zones identified in the AS-IS analysis. LightGBM is used to forecast delay risk following supplier confirmation. Fuzzy logic gates (i.e. FIS) control shipment readiness prior to dispatch. Clustering segments suppliers after delivery to inform future planning and escalation. These interventions are not generic—they are placed exactly at known coordination bottlenecks.

This redesign also restructures coordination ownership. Roles no longer depend on milestone proximity or follow-up vigilance. Instead, procurement, logistics, and transport actors receive filtered outputs generated by embedded analytics. These include readiness scores, delay risk alerts, and segmented supplier classifications. Each role responds to structured triggers, not raw data. This speeds up decisions and strengthens accountability without changing the structure.

The model maintains a human-in-the-loop approach. AI tools guide coordination, but final decisions remain in the hands of users. This was a deliberate choice. During interviews, stakeholders confirmed that automation was neither expected nor desirable. What they needed was early visibility—signals they could trust and act on. To support this, the TO-BE SSB uses lightweight deployment logic. Models operate as Excel scripts, PowerBI dashboards, or SAP exports. No new platform is introduced, and no core system is replaced.

These changes reflect a deeper shift in project coordination philosophy. Instead of governing by milestone and escalation, the TO-BE board governs by flow and signal. This aligns with Lean strategy principles, where value is delivered not through firefighting, but through anticipatory coordination and waste elimination. As Locher (2008) explains, future-state mapping is only successful when information flow, operational control, and system integration are redesigned together. This supports what Ayeni (2025) emphasizes: Lean transformation requires cross-functional alignment and early risk detection—exactly what the redesigned SSB now enables.

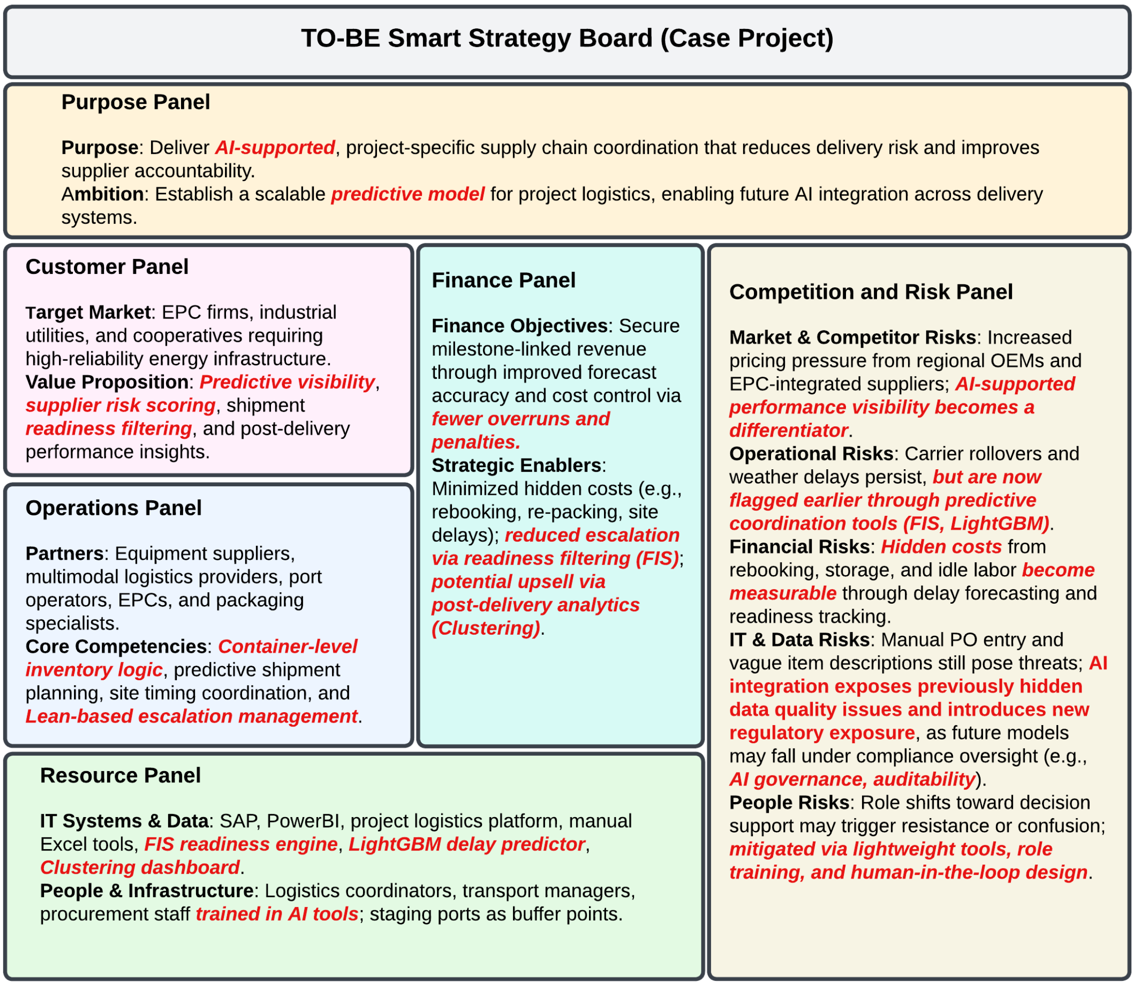

Figure 7.1. TO-BE Smart Strategy Board for the Case Project — AI-Supported Strategic Model.

Figure 7.1 shows the updated SSB. Each of the six panels now reflects a shift in how project goals, risks, operations, and resources are coordinated. Predictive checkpoints replace reactive triggers. Role segmentation replaces vague ownership. Strategic alignment is achieved not by redefining responsibilities, but by making foresight actionable. The next section builds on this logic by presenting the redesigned BMC for the case project.

7.4.2 TO-BE Business Model Canvas

The TO-BE BMC reflects a redefined value creation structure for project delivery. Building directly on the redesigned SSB in Section 7.4.1, it translates predictive coordination logic into operational activities, resource alignment, customer engagement, and revenue structure. While the AS-IS model was reactive and milestone-driven, the TO-BE canvas emphasizes predictive coordination and structured decision support. Value is now delivered not just through equipment, but through the predictability and transparency of the delivery itself.

The revised canvas introduces several structural changes. The value proposition shifts from project completion to reliable, risk-informed delivery. This is enabled by three embedded AI models. LightGBM supports early detection of supplier risk; FIS gates shipment readiness through real-time rule evaluation; and Clustering creates differentiated supplier follow-up after delivery. These tools replace generic process oversight with data-driven coordination checkpoints.

Key activities now include predictive supplier evaluation, readiness filtering, and post-delivery behavior classification. These activities are not siloed—they are mapped directly to roles. Procurement follows up using risk scores instead of calendar thresholds. Logistics teams clear shipments only when readiness signals confirm completeness. Complaint handling becomes forward-looking, drawing on clustering insights to inform future coordination strategy.

Customer relationships and coordination channels have also evolved. The TO-BE model introduces tailored dashboards that give all stakeholders direct access to delivery status and risk information. Communication shifts from reactive clarification to proactive signaling. These updates respond to previously documented coordination delays and visibility gaps in the AS-IS process, where shipment uncertainty and inconsistent documentation led to schedule volatility.

Resources are optimized around integration rather than expansion. The models are deployed using familiar tools such as Excel, PowerBI, and SAP exports, avoiding the need for new platforms or interfaces. This ensures compatibility with existing workflows while upgrading decision support at minimal cost. In parallel, external coordination—especially with suppliers and logistics partners—benefits from the same integration logic by enabling performance-based feedback without adding friction. Strategic partnerships are now managed using supplier segmentation and role-based coordination, increasing both efficiency and accountability. This aligns with the case company's ongoing sustainability goals, where responsible sourcing and Environmental, Social, and Governance (ESG)-linked performance have become increasingly important strategic metrics (Case Company, 2025b).

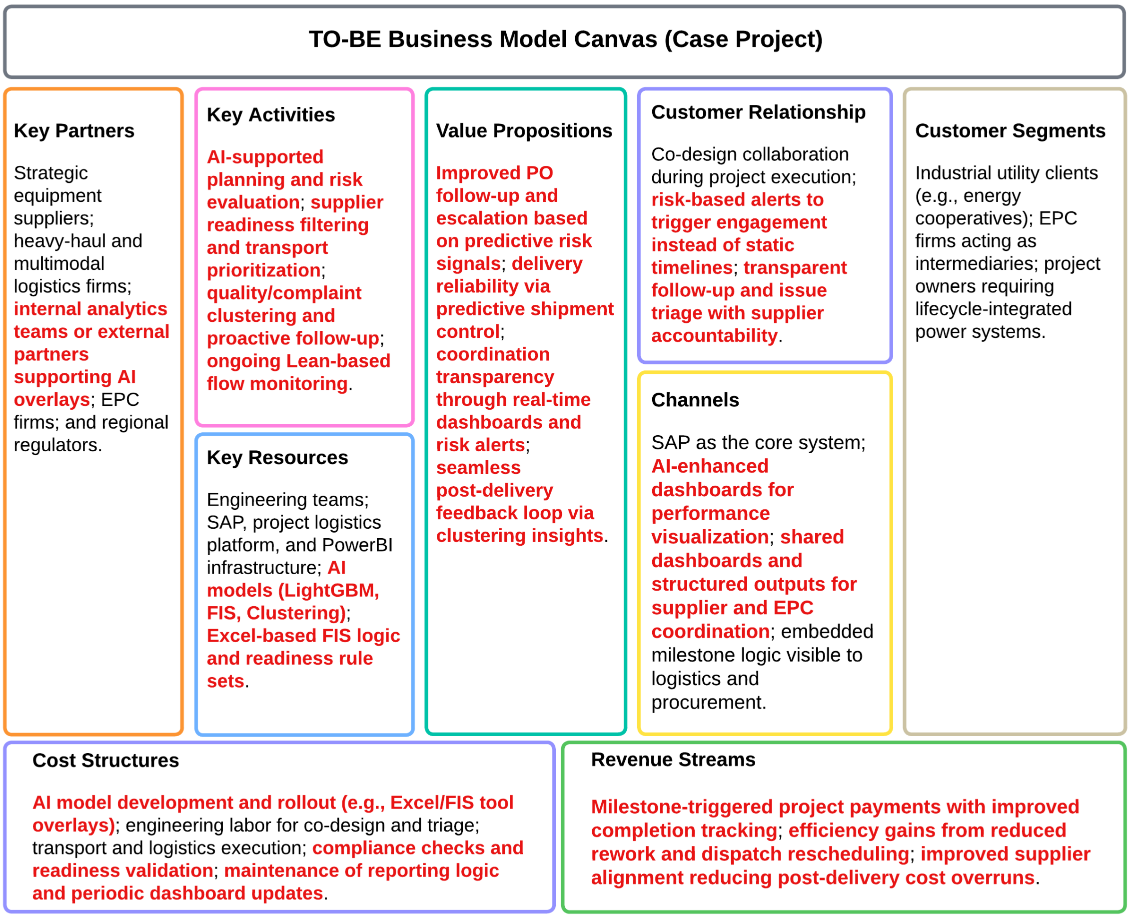

Figure 7.2. TO-BE Business Model Canvas for the Case Project — AI-Integrated Value Logic.

Figure 7.2 visualizes the redesigned BMC. Each block reflects a targeted extension of the AS-IS logic, now enhanced with AI-supported visibility and structured flow logic. As Madanchian (2024) emphasizes, value delivery in complex systems depends not just on resources or tools, but on the ability to make earlier, data-informed decisions in dynamic environments. The TO-BE canvas applies that principle across operational, financial, and coordination domains—aligning predictive intelligence with delivery reliability.

This strategic framing complements the TO-BE SSB by showing how predictive coordination is not just a technical feature but a structural change in how the project creates and delivers value. It also establishes the foundation for the redesigned Value Stream Map presented in the next section.

7.5 Redesigned Value Stream Map

Having established the strategic redesign of project coordination through the TO-BE SSB and BMC, this section now presents the operational translation of that logic in the form of a redesigned Value Stream Map. This map retains the eight-step structure while adding predictive controls and clearer process ownership.

Rather than introducing an entirely new framework, the TO-BE Value Stream Map builds directly on the AS-IS sequence. It embeds decision-support only where there is a validated bottleneck, accessible data, and practical feasibility within the case company's current tooling. This approach maintains continuity while addressing long-standing issues in supplier coordination and delivery control.

Table 7.5 outlines the key design changes in the TO-BE Value Stream Map, linking each enhancement to a specific weakness diagnosed in the AS-IS model.

Table 7.5. TO-BE process enhancements mapped to VSM steps and AI support points.

Step	AS-IS Weakness	TO-BE Enhancement
Step 4	Reactive confirmations; no early warning for delays	LightGBM model flags high-risk POs based on supplier history and confirmation speed
Steps 5–6	Readiness checks based on memory and incomplete fields	FIS applies rule-based scoring to assess shipment readiness before dispatch
Step 8	No structured follow-up or supplier profiling post-delivery	Clustering segments suppliers by delay, defect, and reliability metrics to support escalation planning
VSM Symbols	Kaizen bursts and inventory triangles signal instability	Replaced with AI checkpoints and stable release logic based on predictive inputs

The redesign introduces three categories of enhancements. First, AI checkpoints are embedded at critical steps: LightGBM is placed at Step 4 to flag supplier delay risks; a Mamdani-style FIS controls readiness validation in Steps 5–6; and Clustering is used at Step 8 to segment suppliers based on post-delivery performance. Second, flow stability is improved by removing Kaizen bursts and inventory triangles where AI logic now governs execution—replacing reactive escalation with preemptive control. Visual clarity is enhanced by adding green AI tags at decision points and boxing key performance metrics in green to signal improvement areas.

These visual changes are grounded in Lean thinking. As Rother and Shook (1999) note, Kaizen bursts signify instability in the value stream and should be removed when process maturity is achieved. King and King (2017) explain that inventory triangles in VSM indicate material accumulation points in the process. As Croson et al. (2004) show, such inventory often serves as coordination stock—buffering against misalignment between actors but potentially masking underlying coordination failures. Their removal reflects the shift to readiness-based release logic supported by FIS intervention. The boxed performance metrics remain consistent with those calculated in Chapter 6. Their green framing signals future improvement, based on model-backed projections described in Section 7.3.

Manual information flows—such as quotation handling or PO release—are preserved as thin arrows, while thick arrows continue to indicate physical movement of materials. AI tags appear in green at Steps 4, 6, and 8 to anchor the reader in where the most critical changes occur. These changes transform the delivery process from a milestone-driven timeline into a signal-driven flow, where coordination is guided by data, but still governed by users.

The TO-BE Value Stream Map below consolidates these design shifts. Figure 7.3 presents the redesigned Value Stream Map. It completes the transition from diagnosis to redesign by providing a process-level visualization that reflects both operational logic and strategic intent.

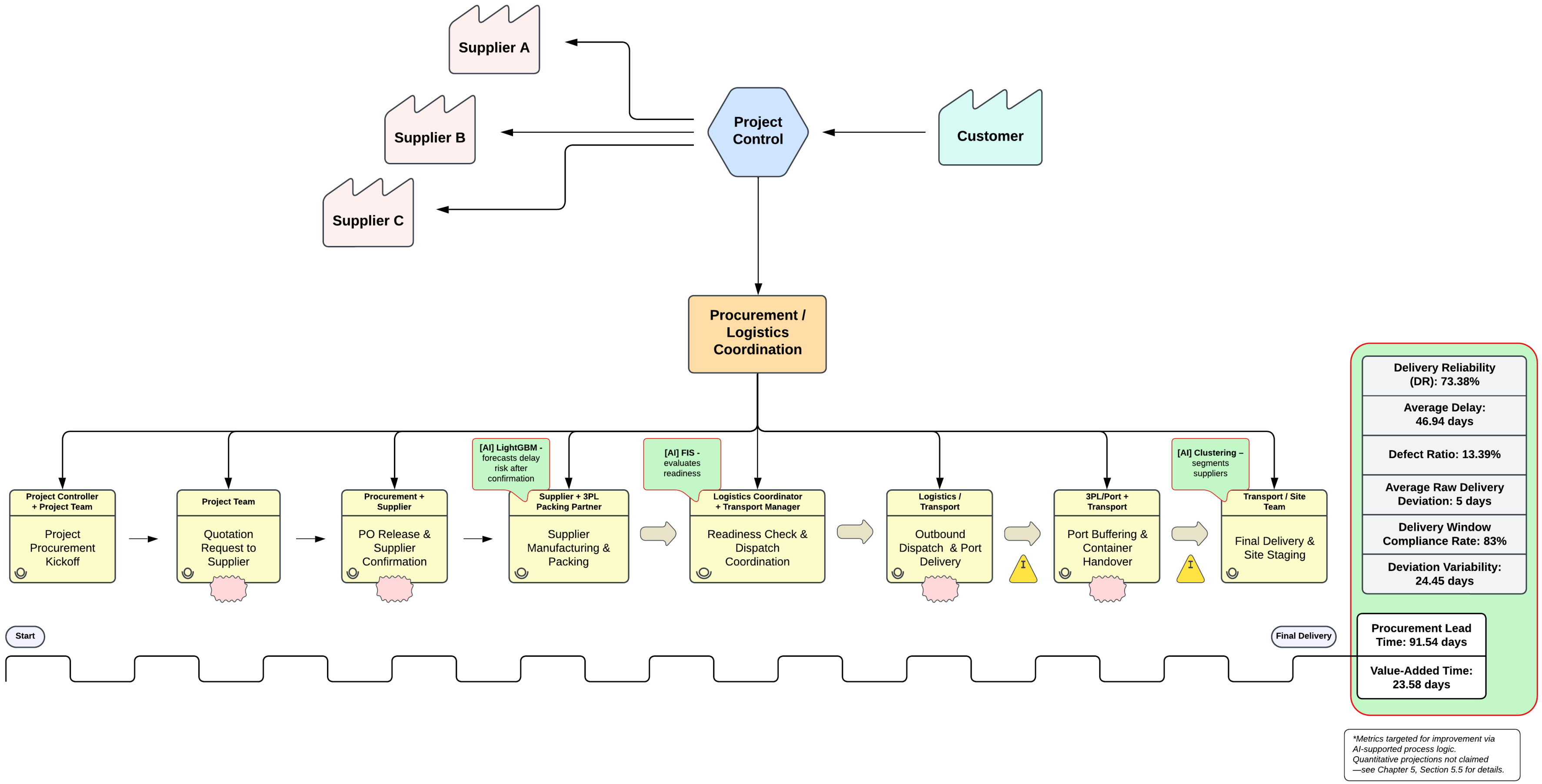

Figure 7.3. TO-BE Value Stream Map – Supplier Coordination Process with AI Integration.

Note: Metrics shown reflect AS-IS values and are boxed in green to indicate improvement targets. Quantitative projections are not embedded—see Section 7.3 for supporting justification.

7.6 AI Feasibility and Rollout Strategy

Section 7.2 established the technical logic behind each AI model and explained how they align with coordination gaps and existing process structures. This section builds on that foundation by evaluating whether those models can be realistically adopted within the case company's operational and cultural environment. It shifts from integration logic to roll-out feasibility—examining organizational readiness, tool maturity, and user expectations. A maturity-based deployment strategy is then proposed to introduce the models in stages, ensuring that adoption is both practical and aligned with current routines. This perspective ensures that the TO-BE Value Stream Map is not only process-aligned but also implementable in practice.

7.6.1 Technical Feasibility Across Existing Systems

As detailed in Section 7.2.3, each AI model was designed to operate within existing workflows using structured data and familiar tools. This subsection confirms that those process-level integrations are technically feasible given the case company's current system landscape.

All three models—LightGBM, FIS, and Clustering—function independently of core ERP systems. They rely on routine exports from SAP, Excel trackers, and PowerBI reports, making them deployable without platform changes. This aligns with the company's current digital maturity, which combines automated data capture with manual coordination routines typical of PDSCs.

Past studies have shown the practicality of these models in similar environments. Sani et al. (2023), Wang et al. (2024), and Pasupuleti et al. (2024) demonstrate that LightGBM can be used in procurement and logistics forecasting with minimal data preparation. Similarly, Berbiche et al. (2024) and Sazvar et al. (2022) confirm that FIS supports readiness decisions in low-automation logistics settings. Mendel (2017) further emphasizes that such models are inherently interpretable and well suited for environments where decision-makers rely on transparent, rule-based systems. For segmentation, Xu et al. (2023) and Pedrycz et al. (2021) validate clustering as a practical tool for behavior profiling in real-world supply chains.

Taken together, this confirms that the TO-BE design is technically viable without additional infrastructure. The next subsection turns to whether these models align with user expectations and decision-making culture.

7.6.2 Human-in-the-Loop Integration and Cultural Alignment

Technical feasibility alone does not guarantee adoption. In project-driven environments, successful AI integration relies on alignment with organizational routines and decision-making norms. Interviews with the strategic purchaser, logistics coordinator, and transport manager confirmed that while there is openness to data-driven tools, there is also a clear preference for maintaining human control over key decisions. The models proposed in the TO-BE design respect this need by functioning as assistive layers—providing timely signals without enforcing automated outcomes.

This preference is most evident in how shipment readiness is currently handled. The logistics coordinator emphasized that dispatch decisions are based on personal judgment and context, often informed by informal updates and document checks. A fully automated system would likely face resistance. By contrast, the proposed FIS model offers structured support using logic-based scoring while preserving user control. Tang and Ahmad (2024) note that Mamdani-type fuzzy systems are especially effective in such settings. Their rule sets are accessible and intuitive, enabling domain experts to validate decisions and communicate reasoning without mediation. This makes them ideal for contexts that favor transparent, human-guided decision-making over automation.

Similar preferences were expressed regarding supplier follow-up and delay detection. The strategic purchaser welcomed the idea of delay risk alerts but cautioned that any model output must be transparent and actionable. Black-box models would not be accepted unless they could be explained in business terms. This aligns with the vision outlined in Supply Chain 5.0 frameworks, where AI is seen not as a replacement for human roles but as an enhancement of coordination capability (Boudouaia et al., 2024).

However, caution remains necessary. Hangl et al. (2022) and Übellacker (2025) note that user resistance, job security concerns, and change fatigue are common barriers in early-stage AI deployments. These factors were echoed in the case company, particularly in the transport domain, where any tool that interferes with current scheduling routines would likely be met with skepticism. To mitigate this, all three models are introduced with role-specific triggers and retain the option for user override.

In this way, the TO-BE design reinforces cultural alignment without sacrificing coordination improvement. Each AI model is designed not to dictate decisions, but to support them—making human-in-the-loop governance a central feature of the roll-out plan.

7.6.3 Phased Rollout Strategy for AI Deployment

To make implementation successful, the AI models should be introduced in steps. The process begins with simple tools and moves toward more advanced systems as users become more confident and the organization becomes ready. This approach minimizes disruption while ensuring each model delivers value in a form that teams can understand and trust. Table 7.6 summarizes how each model can be introduced during the early stages using lightweight tools that match current workflows.

Table 7.6. Proposed Rollout Strategy for Artificial Intelligence Integration by Model.

Model	VSM Step(s)	Deployment Format	User Interface	Frequency	Goal in Initial Phase
LightGBM	Step 4	Excel or PowerBI overlay	Risk dashboard with color-coded alerts	Weekly	Flag likely delayed POs for early follow-up
FIS	Steps 5–6	Checklist logic via Excel or web form	GO/NO-GO readiness recommendation	Per shipment	Prevent premature or unready dispatches
Clustering	Step 8	Periodic segmentation report	Supplier grouping dashboard or visualization	Monthly or Quarterly	Adjust coordination effort based on supplier classification

In Phase 1, models are shared using familiar tools—Excel, PowerBI, and manual exports—ensuring compatibility with current routines. LightGBM risk scores can be shown in Excel or PowerBI using SAP-exported data. FIS can be used as a structured checklist in the same logistics templates already in use. Clustering results can be shared as basic supplier reports or color-coded tables. These tools provide predictive support without changing how coordination happens.

As familiarity increases, the second phase introduces light integration. FIS checklists can be moved to browser-based forms. Risk alerts can be delivered through dynamic dashboards with automatic updates. Scripts can be scheduled weekly or monthly to generate new outputs with minimal manual work. This adds structure without removing user control.

The final phase moves toward embedded systems. At this point, risk scores and supplier classifications could be shown directly in SAP. Models could trigger alerts or recommendations inside workflow tools. This level of integration is only introduced once teams are ready and the underlying data quality is stable.

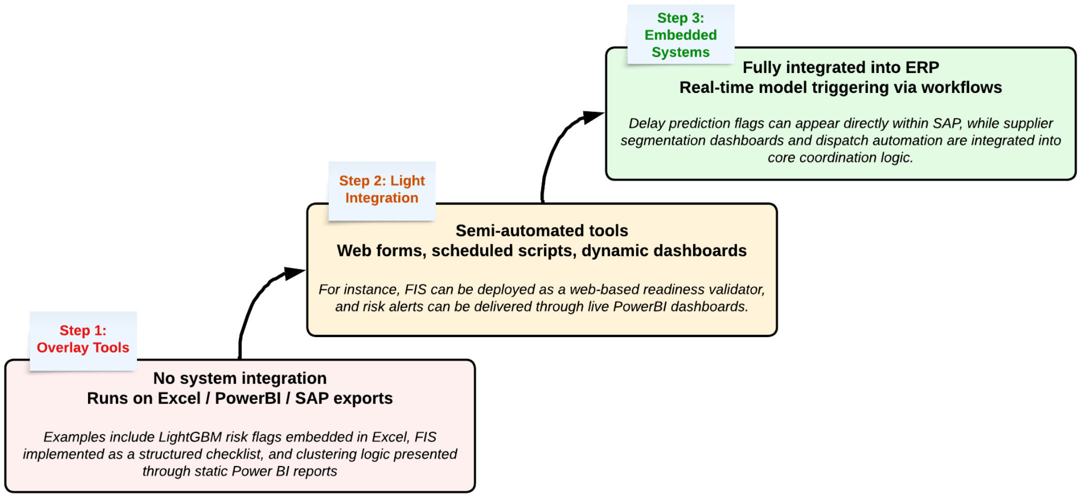

Figure 7.4. Three-stage AI integration path for project-driven supply chains.

Figure 7.4 shows this three-stage roll-out. Each step builds on what is already familiar—starting with Excel, moving to lightweight forms and dashboards, and ending with deeper system connections. The goal is to match technical maturity with organizational readiness and avoid introducing tools that are either too complex or too disconnected from real work. This phased strategy ensures that AI becomes a support layer for coordination—not a disruption. It also respects the company's current tool-set and decision culture, making each step realistic, useful, and aligned with how work actually happens.

Chapter 8

Conclusion and Strategic Project Management Implications

This final chapter consolidates the findings of the research and reflects on their strategic significance. It summarizes the contributions of the thesis, discusses how the redesigned coordination model supports project governance, outlines recommendations for implementation, and presents limitations and future directions. The aim is to show how data-driven coordination, supported by Artificial Intelligence (AI), can reshape supplier delivery performance in Project-Driven Supply Chains (PDSCs)—both in theory and practice.

8.1 Summary of Research and Key Contributions

This thesis set out to answer a practical question: how can AI models be integrated into PDSCs to improve supplier delivery reliability? The research began with a real case project marked by weak coordination and inconsistent delivery execution. Using an abductive and design science–driven approach, the study traced these issues step by step—starting from how information and materials currently flow, and moving toward a redesigned coordination model based on targeted improvement.

The AS-IS Value Stream Map revealed multiple breakdowns across the coordination process. Supplier follow-up lacked structure, and readiness decisions were made based on assumptions rather than verified data. These weaknesses were quantified using a set of eight coordination performance metrics, including Delivery Reliability (73.38%) and average delay (46.94 days). Quality issues were flagged at the site but rarely used to inform future procurement. These findings were validated through interviews, where staff confirmed that the observed pain points reflect normal project operations rather than outliers.

Instead of proposing automation, the research focused on adding predictive insight to points of low visibility. The selected AI models—LightGBM, Fuzzy Inference System, and Clustering—were each matched to a different coordination gap. Their placement came before the redesign, serving as inputs for how the future-state flow should work. This led to a TO-BE Value Stream Map that preserved the existing structure but introduced focused improvements based on data signals and stakeholder feedback.

The framework was built using real data and tested for feasibility within the company's current tools and culture. It avoids system overhauls and shows that smart coordination is possible even when digital maturity is limited. Each model works as a support layer, offering insight without removing user control.

Theoretical contributions include adapting Value Stream Mapping (VSM) to high-variance project supply chains and demonstrating how AI can function in practical, role-specific ways. On the practical side, the outcome is a replicable coordination framework that other firms with similar delivery challenges can adopt using tools they already have. The work connects diagnostic mapping with model-based foresight, showing how better delivery reliability can be achieved without complexity.

8.2 Strategic Project Management Implications

Integrating AI-supported coordination into a project supply chain is not only a technical shift—it is a strategic one. The redesigned process repositions how decisions are made, how roles interact, and how visibility is distributed across functions. What was previously a reactive chain of updates now becomes a flow of signals. Procurement and logistics are no longer silos but interdependent roles operating from the same view of delivery risk and readiness.

This shift creates a foundation for proactive project governance. Instead of responding to issues as they surface, teams can now act based on predictive triggers. The TO-BE Value Stream Map introduces decision-support logic into the flow itself. It provides early warnings, structured readiness checks, and segmented follow-up—all aligned with day-to-day decision points. This reflects what Alam and Gühl (2022) describe as a core element of modern project governance: synchronized control across roles through better visibility.

The AI tools introduced in this thesis are not complex or abstract. They are lightweight, easy to use, and designed for interpretability. They were not built to replace decision-makers but to support them. Siegel (2020) notes that in complex engineering environments, success depends more on accessible insight than on full automation. The models here—whether used in Excel, PowerBI, or SAP exports—offer exactly that. They help project professionals act earlier, with less friction, and with greater confidence in the decisions they already own.

The same logic applies to how these tools are deployed. The roll-out strategy follows the maturity of the organization. Teams do not need to switch platforms or adopt enterprise AI suites. They start small—with file-based inputs, dashboards, or templates—and scale when ready. This approach was confirmed in stakeholder interviews. Procurement professionals emphasized that targeted changes are more realistic than broad system replacements. Alsheyadi et al. (2024) show that strategic supply performance depends not only on digital systems, but on how insights are translated into coordinated action. Their study confirms that performance improves when internal and external supply chain activities are implemented in a synchronized way. This thesis provides a path to do exactly that.

Strategic gains in project environments rarely come from single innovations. They come from shifting how teams see, decide, and respond under pressure. By embedding AI into these coordination moments—not outside them—the redesigned process makes delivery performance a managed outcome, not a moving target. That is the strategic value of this work.

8.3 Recommendations and Implementation Strategy

This section presents targeted recommendations developed from the research findings, aimed at improving supplier coordination and delivery performance, as well as overall supply chain resilience within the case company. It first discusses the strategic evolution needed in supplier evaluation practices, followed by practical actions that can be implemented incrementally to support these goals within the company's operational structure.

8.3.1 Improving Supplier Evaluation Practices

Traditional supplier evaluation systems focus on stable metrics—cost, delivery reliability, and defect rates. These indicators offer clarity in controlled settings, but they fail to capture the complexity of project-based supply chains. When engineering needs change and timelines shift, supplier responses become harder to predict. In such cases, static KPIs can mislead rather than inform.

To manage uncertainty, supplier evaluation needs to reflect behavior, not just output. This thesis showed that adaptability under pressure often reveals more about supplier value than static averages. In the case project, delayed confirmations and reactive follow-ups were not captured in traditional KPIs, yet they consistently disrupted coordination. These findings support the need to move beyond rigid scorecards toward flexible evaluation logic—capable of capturing real-time patterns and supplier responsiveness in shifting project conditions. A similar logic was used in a recent project by the author. The work developed and evaluated an AI assistant for industrial machine operators using retrieval-augmented generation and few-shot learning to support decision-making under evolving conditions and limited information (Ibrahim & Ibrahim, 2024).

Fuzzy logic offers that flexibility. Unlike deterministic models that expect clean, complete data, fuzzy approaches tolerate ambiguity and make it actionable. Fagundes et al. (2021) demonstrate how fuzzy Analytic Hierarchy Process (AHP) can support supplier prioritization even when data is inconsistent or subjective. This makes it especially suited for project contexts, where judgment, timing, and partial information drive decisions.

AI builds further on this logic. Nandi et al. (2024) show how small behavioral signals—like repeated confirmation delays or unstable lead times—can flag disruption risk before it shows up in KPIs. Walter (2023) expands on this with evidence that AI models can uncover patterns across fragmented datasets, offering early warnings that humans may miss. A supplier scoring model is only useful if it helps people act—not if it hides insight in technical abstraction.

Sustainability is another axis of change. As ESG criteria become embedded in procurement strategy, evaluation methods must adapt. Qu and Kim (2024) argue that integrating environmental and ethical dimensions requires systems capable of parsing unstructured, non-financial data. AI can support this by extracting meaningful signals from diverse sources, making it easier to assess not just what a supplier delivers, but how.

Altogether, the case company stands at a point where continuing with legacy evaluation frameworks limits both insight and action. Moving toward AI-supported models—resilient and aligned with sustainability—is not about replacing what works. It is about uncovering what legacy metrics fail to reveal.

8.3.2 Steps for Implementation

Translating evaluation improvements into operational change requires more than model selection. It calls for practical, tool-compatible steps that teams can scale with confidence. The case company operates in a fast-paced, project-driven environment. This makes focused interventions more viable than sweeping reforms. Each recommendation presented here reflects that reality.

Stakeholder interviews confirmed a clear preference for improvements that align with existing workflows. Procurement teams favored pilots built in Excel or PowerBI. Logistics coordinators emphasized the need for interpretable outputs and minimal overhead. These preferences shaped the roll-out logic embedded in the TO-BE design and confirmed that AI integration must enhance—not interrupt—daily decision-making.

The actions recommended below are designed to work within this context. They do not require new platforms or technical expertise. Instead, they use what is already in place: familiar coordination routines, existing data exports, and role-specific knowledge. Each action strengthens a known gap by adding a structured layer of support—whether for risk detection, supplier tracking, or process follow-up. The discussion above outlines the broader context and constraints for implementation. Table 8.1 then presents specific, actionable steps tailored to that reality.

Table 8.1. Recommended implementation actions for AI-supported supplier coordination.

Action	Purpose	Operational Fit
Pilot FIS-based readiness scoring	Evaluate how fuzzy logic can flag incomplete shipments before dispatch	Feasible using Excel or PowerBI; validated in interviews; requires no system integration
Apply clustering in supplier review cycles	Segment suppliers by behavior to guide differentiated follow-up	Uses existing delivery and quality data; enhances planning without real-time requirements
Create a "digital coordinator" role	Interpret AI outputs and connect procurement with logistics in real time	Bridges current coordination gap; supports role clarity without structural reorganization
Integrate model outputs into the Smart Strategy Board	Ensure predictive signals inform planning, not just execution	Aligns with current project governance tools; enhances strategic foresight
Facilitate cross-functional VSM workshops	Refine coordination flows through shared mapping sessions	Encourages real-time collaboration; validated method for surfacing inefficiencies

Together, these actions reflect a maturity-aligned approach to AI integration. As shown in the rollout framework in Subsection 7.6.3, the path begins with overlays, continues through light automation, and ends in embedded decision support. These steps also reinforce governance principles outlined by Morris and Pinto (2007), where project alignment depends on the tight coordination of operational routines with strategic planning. The recommendations are not just process tweaks. They are decision enablers—small shifts with long-range impact.

8.4 Limitations

This research prioritized depth of analysis within a single case context over broad generalizability. Its findings are grounded in a single case project within one organization. While this allowed a focused and realistic analysis, it also limits how far the results can be generalized. Other companies, especially those in different sectors or with different project models, may face coordination challenges that require separate evaluation.

The AI models proposed were not deployed in live operations. Their logic was tested through simulations and validated in interviews, but real-world performance remains unmeasured. This means their projected impact is based on how well they fit observed problems—not on hard performance metrics. That said, each model was placed based on actual data and reviewed with stakeholders for feasibility. The design is realistic, but its effectiveness will depend on future pilots.

The scope of the research was intentionally narrow. It focused on the supplier delivery flow, which is critical in PDSCs but only one piece of the broader coordination puzzle. Internal handovers, customer-side delays, and inter-project dynamics were not included. These were excluded to maintain clarity and focus within the available time-frame and data access.

These limits don't reduce the value of the framework. They define where it starts. Future work can extend this baseline—through live testing, cross-project comparison, or integration with customer and internal flows—to build a more complete picture of how AI can support project coordination at scale.

8.5 Future Directions and Outlook

This thesis creates a starting point, not a conclusion. While the models were conceptually validated and placed into a redesigned coordination structure, their true potential will only emerge through application. Future research should begin with field-testing the proposed AI components: LightGBM for delay prediction, FIS for shipment readiness, and Clustering for supplier segmentation. Testing these in live environments will reveal not only their accuracy, but also how well they integrate with project workflows under pressure.

Beyond validation, new use cases should be explored. Cross-functional delay prediction, packaging quality control, or internal handover forecasting could extend the impact of this framework.

These applications would require linking complaint records or exception reports to early indicators—transforming follow-up into prevention. Comparative research across project types—ETO, modular builds, or serial production—would also help determine how transferable this coordination logic is. Such contexts offer fertile ground for cross-case insights into how AI can support visibility and coordination.

Longer-term, these models could evolve from standalone tools into integrated elements within project dashboards or Smart Strategy Boards (SSBs). They would shift coordination from milestone tracking to signal-based management. Instead of isolated decisions, functions across the supply chain would operate from a shared understanding of delivery risk. What matters most in these environments is not the volume of data, but the ability to access the right insight at the right moment. Embedding AI into existing platforms can make that possible—without adding complexity or disrupting existing routines.

This vision extends into more interactive systems. Inspired by voice-guided operations already in use on factory floors, future decision-makers could interface with AI using natural questions. A project manager might ask:

> *"Which suppliers are likely to delay shipments this week?"*
>
> *"What's the predicted lead time for PO 452128?"*
>
> *"Why was container 1042 delayed in week 15?"*

These conversational interfaces would bridge the gap between analytics and strategic action, removing friction, not adding layers. Decision tools must support governance and enable coordination, not operate in isolation. Responsive supply chains depend on technologies that embed coordination directly into operations.

Rather than promising full automation, this thesis positions AI as a support layer. It helps people gain foresight and make timely, confident decisions. The TO-BE model presented here is not just a process redesign—it is a blueprint for shifting from reactive firefighting to proactive, value-driven project delivery. That shift is not theoretical. It is ready to begin.

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Appendices

Note: All calculations, logic definitions, and dataset interpretations presented in this and subsequent appendices were developed by the author based on anonymized internal case project data.

Appendix 1. Metrics Calculation Methodology

Procurement Lead Time (PLT) Calculation

Definition

PLT is defined as the number of calendar days between the creation of a PO and the date the ordered goods are considered ready for delivery or received by the buyer. It reflects the supplier's total lead time including preparation, confirmation, and production before handover or delivery.

Data Sources

The following fields were used from Dataset A (PO Log) and Dataset B (Delivery Validation):

- **PO Creation Date** – The original date when the PO was issued in SAP (Dataset B).
- **Confirmed Delivery Date** – The date the supplier promised delivery (Dataset B).

- **Calculated GR Date** – The date the case company confirmed receipt of goods in the system (Dataset B).
- **Incoterm** – Indicates delivery responsibility and was used to determine which date to consider as the delivered point (Dataset B).

Applied Logic

The logic for calculating PLT was guided by the case company's official delivery reliability definitions (Dataset G). According to these, the correct date to use for delivery depends on the agreed Incoterm:

- For **DAP/DDP** deliveries: PLT = Calculated GR Date – PO Creation Date.
- For **FCA** deliveries: PLT = Confirmed Delivery Date – PO Creation Date.

Implementation

Each row in the final PLT dataset was constructed by extracting and aligning PO numbers, item positions, Incoterms, and relevant dates. Based on Incoterm logic:

- If Incoterm = DAP or DDP, the GR Date (Confirmed Goods Receipt) was used as the delivery point.
- If Incoterm = FCA, the Confirmed Delivery Date was used as a proxy for Document Date (Ready for Pick-up).

The PLT was calculated in Excel using:

```
=IF(OR(Incoterm="DAP"; Incoterm="DDP");
   GR Date;
   Confirmed Delivery Date)=Final Delivery Date – PO Creation
      Date
```

After calculation, rows were filtered to exclude blanks and any PLT values less than zero. Out of 252 total PLT rows, 246 were retained as valid for final analysis.

Result

The final recalculated average Procurement Lead Time was **91.54 days**, based on 246 valid rows. This value is considered the most reliable and traceable result after filtering and aligning with official case company Incoterm-based delivery definitions.

Limitations

Document Date was not directly available in the dataset and was approximated using Confirmed Delivery Date. While this is a reasonable proxy, it may slightly underestimate PLT in some FCA deliveries. Additionally, a small number of entries with invalid or missing data were excluded to ensure data integrity.

Delivery Reliability (DR) Calculation

Definition

DR refers to the percentage of deliveries that arrive on or before the expected delivery date, within a defined grace period. For this analysis, the grace period was set to **2 calendar days**, in line with the case company's official delivery reliability policy (Dataset G and Dataset H).

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Statistical Delivery Date** – The planned delivery date based on initial purchase order agreement.

- **Confirmed Delivery Date** – The date confirmed by the supplier as the actual delivery date (used for FCA).
- **Calculated GR Date** – The date goods were received and registered by the case company (used for DAP/DDP).
- **Incoterm** – Used to determine which actual delivery date to compare against the statistical plan.

Applied Logic

According to the case company’s internal rules:

- For **FCA** deliveries, the Confirmed Delivery Date was used.
- For **DAP/DDP** deliveries, the Calculated GR Date was used.

Each delivery was marked as “on time” if the actual delivery date was less than or equal to the Statistical Delivery Date plus two days.

The check was performed using the following logic in Excel:

The check was performed using the following logic in Excel:

```
=IF(OR(Incoterm="DAP"; Incoterm="DDP");
   GR Date;
   Confirmed Delivery Date)=IF(Delivered Date <= Statistical
      Delivery Date + 2;
   "Yes";
   "No")
```

Result

Out of all deliveries evaluated, **73.38%** were determined to be on time. This result reflects a reasonable level of delivery performance but indicates room for improvement, particularly in early warning systems or supplier coordination.

Limitations

In some cases, delivery records may have had inconsistencies between planned and confirmed dates due to lack of updated confirmations in the project logistics platform. Additionally, a small number of rows were excluded due to missing date values or Incoterm mismatches, but these were minimal and did not materially affect the final result.

Delivery Delay Calculation

Definition

Delivery delay refers to the number of calendar days between the planned delivery date and the actual delivery date of a shipment. It is used to quantify how far behind schedule a delivery was when it failed to arrive on time. Only delayed deliveries (i.e., those arriving after the planned delivery date) were included in this calculation.

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Statistical Delivery Date** – The expected delivery date based on the purchase order agreement.
- **Confirmed Delivery Date** – The supplier's stated readiness or dispatch date (used for FCA).

- **Calculated GR Date** – The date the case company confirmed receipt of the shipment (used for DAP/DDP).
- **Incoterm** – Used to select which delivery date source to apply for delay calculation.

Applied Logic

Following the case company's delivery reliability policy (Datasets G and H):

- For **DAP/DDP** deliveries, the delay was calculated as:
  `GR Date { Statistical Delivery Date`
- For **FCA** deliveries, the delay was calculated as:
  `Confirmed Delivery Date { Statistical Delivery Date`

This logic was implemented using a conditional Delivered Date column that selected the appropriate actual delivery date based on Incoterm. Delay in days was then calculated as:

```
=IF(OR(Incoterm="DAP"; Incoterm="DDP");
   GR Date;
   Confirmed Delivery Date)=Delivered Date - Statistical
      Delivery Date
```

Result

Out of all deliveries with valid statistical and actual delivery dates, the calculated average delay for late deliveries was **46.94 days**. This reflects the average number of calendar days that late deliveries were behind schedule.

Limitations

Dataset B contains a pre-calculated column “Days late (GR-StatDD)“, which calculates delay based solely on the GR Date. However, this field does not account for Incoterm rules, and thus cannot be reliably used for all delivery types. For this reason, a custom Delivered Date column was created and used in accordance with the case company’s policy.

Value-Added Time (VAT) Calculation

Definition

VAT refers to the number of calendar days between when a supplier marks goods as ready for pick-up and when the case company officially receives them. This metric captures the time taken for transportation, logistics coordination, and final goods receipt.

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Confirmed Delivery Date** – Used as a proxy for the Document Date, representing when the supplier marked the goods as ready.
- **Calculated GR Date** – Represents the Goods Receipt date (also known as Posting Date) in the case company’s SAP system.

Applied Logic

The logic for calculating VAT was derived from the case company’s delivery documentation (Datasets G and H), which defines:

- **Document Date** – The date supplier marks shipment as “Ready for pick-up” in the project logistics platform.
- **Posting Date** – The date the case company logs Goods Receipt based on the same system.

Since the exact Document Date was not available, the Confirmed Delivery Date was used as a proxy. The VAT value was calculated in Excel using:

```
=IF(AND(ISNUMBER(GR Date);
       ISNUMBER(Confirmed Date);
       GR Date >= Confirmed Date);
   GR Date - Confirmed Date;
   "")
```

Values less than 0 were excluded, as these would indicate data or system entry errors.

Result

The final average VAT was calculated as **23.58 days**, based on all valid rows with non-negative VAT values. This reflects the typical time window between goods being marked ready by the supplier and officially received by the case company.

Limitations

The Confirmed Delivery Date is not always equivalent to the true Document Date, which is system-generated in the project logistics platform. In this analysis, it was used as a best-available proxy due to dataset constraints. This approximation may slightly understate VAT in some cases. Additionally, rows with missing or invalid dates were excluded to ensure integrity.

Defect Ratio Calculation

Definition

Defect Ratio measures the proportion of received deliveries that were affected by quality-related issues, such as those requiring Quality Error (QE), Quality Verification (QV), or Field Fault (XF). It is expressed as a percentage of all successfully received lines (i.e., lines with a valid Goods Receipt date).

Data Sources

The following fields and datasets were used:

- **Dataset C (Notification Log)** – Used to identify all defect-related notifications. Only notifications of type `QE`, `QV`, and `XF` were included.
- **Dataset B (Delivery Validation)** – Used to determine the total number of PO lines that resulted in a valid Goods Receipt (via the Calculated GR Date field).

Applied Logic

The Defect Ratio was calculated using the following formula:

```
Defect Ratio =
    (Number of QE + QV + XF notifications) / (Total GR lines
        received) * 100%
```

Only PO lines with a non-empty Calculated GR Date were considered received. The final count of defect notifications was determined by counting all notifications in Dataset C where the `Type` field was either `QE`, `QV`, or `XF`.

Result

A total of 32 defect-related notifications were found (30 XF and 2 QE), and 239 PO lines were identified as having a valid Goods Receipt. This yields a final Defect Ratio of **13.39%**.

Limitations

Some notifications may have been linked to multiple GR lines or reported against broader project elements rather than individual PO line items. Additionally, the Confirmed Delivery Date was not used to cross-validate against notification timing, which could impact deeper cause-effect analysis. However, the defect count reflects the best available approximation of delivery-level quality issues.

Raw Delivery Deviation Calculation

Definition

Raw Delivery Deviation measures the difference in calendar days between the planned delivery date and the actual delivery date, regardless of whether the delivery was early or late. It reflects how closely supplier deliveries align with the original schedule and is used to evaluate consistency across all deliveries.

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Statistical Delivery Date** – The planned delivery date based on the initial PO agreement (Dataset B).
- **Confirmed Delivery Date** – The supplier's stated readiness or shipment date (used for FCA, Dataset B).

- **Incoterm** – Used to confirm the delivery condition; nearly all entries were FCA (Dataset B).

Applied Logic

Given that 99.99% of rows had an Incoterm value of FCA, only those were included in the deviation calculation. According to the case company's delivery policy, FCA deliveries use the Confirmed Delivery Date as the effective delivery date.

Deliveries were filtered using the following conditions:

- Incoterm = FCA
- Statistical Delivery Date is not blank
- Confirmed Delivery Date is not blank

The deviation was calculated using:

```
=Confirmed Delivery Date − Statistical Delivery Date
```

This formula returns a positive value for late deliveries, a negative value for early deliveries, and zero for on-time deliveries.

Result

A total of 215 valid rows were included in the final calculation. The average Raw Delivery Deviation was **5.00 days**. This value reflects the mean difference between planned and actual delivery dates for all filtered FCA rows.

Limitations

This metric is highly dependent on Confirmed Delivery Date accuracy. Minor human entry errors or supplier updates not reflected in SAP could distort specific rows. Additionally, early deliveries result in negative values, which were preserved in the calculation to reflect full deviation behavior.

Delivery Window Compliance Rate Calculation

Definition

Delivery Window Compliance Rate refers to the percentage of deliveries that arrived within an acceptable time window around the planned delivery date. It provides a more nuanced view of delivery performance than a strict on-time metric by allowing for a defined range of early or late arrival.

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Statistical Delivery Date** – The planned delivery date based on the original PO (Dataset B).
- **Confirmed Delivery Date** – The supplier-confirmed delivery date (used for FCA, Dataset B).
- **Incoterm** – Used to filter for FCA-only deliveries, as per case company policy (Dataset B).

Applied Logic

This metric was calculated only for rows with:

- Incoterm = FCA
- Statistical Delivery Date is not blank

- Confirmed Delivery Date is not blank

Deliveries were considered “compliant” if they occurred within a window from 1 day early to 2 days late relative to the Statistical Delivery Date. The following Excel formula was used:

```
=IF(AND(Confirmed Delivery Date – Statistical Delivery
   Date >= -1;
Confirmed Delivery Date – Statistical Delivery Date <= 2);
    1; 0)
```

The compliance rate was then calculated using the AVERAGE function over the filtered values.

Result

The final Delivery Window Compliance Rate was **83%**, based on all FCA deliveries with valid dates. This result indicates a high level of delivery precision within a narrow 3-day range centered on the planned schedule.

Limitations

This metric assumes that deviations of ±1 to 2 days are acceptable, based on project flexibility and case company expectations. The threshold could be adjusted for stricter or more lenient tolerance depending on project context. Also, rows with blank or non-FCA entries were excluded from the analysis.

Deviation Variability (per Supplier) Calculation

Definition

Deviation Variability measures the consistency of a supplier’s delivery performance by calculating the standard deviation of delivery deviations (in days) across all deliveries linked to that supplier.

A higher value indicates greater inconsistency, while a lower value reflects more stable delivery behavior.

Data Sources

The following fields were used from Dataset B (Delivery Validation):

- **Supplier** – Identifies the vendor associated with each delivery (Dataset B).
- **Statistical Delivery Date** – The planned delivery date used as a reference (Dataset B).
- **Confirmed Delivery Date** – The actual delivery date, as confirmed by the supplier (Dataset B).
- **Incoterm** – Used to isolate FCA deliveries for standard comparison (Dataset B).

Applied Logic

The dataset was filtered using the following rules:

- Incoterm = FCA
- Statistical and Confirmed Delivery Dates must not be blank
- Supplier field must not be blank

For each remaining row, the raw delivery deviation was calculated as:

```
=Confirmed Delivery Date – Statistical Delivery Date
```

The filtered list of deviations and their associated suppliers were used to create a Pivot Table in Excel. The table was configured as follows:

- **Rows** – Supplier

- **Values** – Standard Deviation of Raw Delivery Deviation (days)

Suppliers with only one delivery were automatically excluded from the result, as standard deviation requires at least two values.

Result

The resulting pivot table revealed distinct differences in delivery consistency across suppliers. Suppliers with higher standard deviation values demonstrated more erratic delivery behavior, while others showed consistently narrow deviation windows. The resulting variability values were used to support supplier segmentation and clustering recommendations in Chapter 5.

The overall average deviation variability across all suppliers was **24.45 days**. This reflects the typical spread in delivery performance and reinforces the need for segmentation strategies that account for behavioral inconsistency.

Limitations

Some suppliers had only one valid delivery, making it impossible to calculate standard deviation—these were returned as `#DIV/0!` and excluded. Additionally, Confirmed Delivery Date was used as a proxy for actual delivery timing, which may not fully reflect on-site delivery outcomes. Nonetheless, the variability values serve as a strong relative indicator of supplier consistency.

Appendix 2. FIS Readiness Filtering Methodology

Objective

This appendix outlines the methodology used to simulate how a FIS) could have filtered out unqualified shipments at Steps 5–6 of the TO-BE Value Stream Map. The goal is to establish a traceable connection between the qualitative logic of the FIS and actual coordination challenges observed in the Case Project.

Data Sources

The simulation was based on Dataset D *(Shipment Cases)* provided by the case company. Key fields utilized include:

- **Packing Material Weight** –Indicates whether packaging was fully prepared for shipment.
- **Checked Load Weight** –Reflects final logistics validation status before dispatch.
- **Case added to unused materials** –Suggests rollback or repacking after dispatch.

Logic Applied for Simulation

To simulate the impact of the FIS, three bottleneck scenarios it was designed to prevent were defined:

1. **Incomplete Packaging Cases:** Rows where either *Packing Material Weight* or *Checked Load Weight* was missing (”-”).
2. **Missing Documentation Cases:** Rows where *both* of the above fields were missing, indicating high risk of readiness failure.

3. **Repack or Blocked Cases:** Rows where *Case added to unused materials* was populated, suggesting intervention or rework occurred.

The logic was implemented using Excel formulas to filter these rows:

```
=OR([@[Packing Material Weight]]="-", [@[Checked Load Weight
   ]]="-")
=AND([@[Packing Material Weight]]="-", [@[Checked Load Weight
   ]]="-")
=[@[Case added to unused materials]]<>"-"
```

Simulation Dataset Construction

Each filtered group was exported as a separate Excel file:

- `FIS_Simulation_IncompletePackaging.xlsx`
- `FIS_Simulation_MissingDocs.xlsx`

No repacking cases were identified in the available dataset (0 rows matched). All filters and data processing steps were conducted using structured logic and string comparison within Excel.

Resulting Frequencies for Table 7.4

The following frequencies were derived and applied in the simulation:

- **Incomplete Packaging:** 5815 cases
- **Missing Documentation:** 4824 cases
- **Repacking / Blocked Dispatch:** 0 cases

Limitations

Although real shipment data was used, the cases were flagged based on field completeness rather than confirmed operational errors. This simulation assumes that missing packaging or documentation data represents coordination risk consistent with observed issues in the AS-IS process. As such, the simulation offers realistic but non-validated projections.

Validation Summary

This analysis supports the feasibility of using FIS to block low-readiness shipments based on structured field logic. It bridges qualitative TO-BE logic with actual case project shipment conditions and serves as a traceable basis for the simulated coordination improvements presented in Chapter 7.