The present work was submitted to:
Chair of Process and Data Science
RWTH Aachen University

Combining Process Mining and Inventory Management by using Quantity Event Log (QEL) to Identify and Visualize Key Metrics

Bachelor Thesis

presented by

Ahmad Noureddin Mannoun
437528

First Examiner: Prof. Dr. Wil M. P. van der Aalst
Second Examiner: Prof. Sander J. J. Leemans

Advisor: Nina Graves

Aachen, March 19, 2025

Acknowledgments

Abstract

In the domain of inventory management, particularly within logistics, organizations face the challenge of maintaining optimal stock levels while minimizing hidden costs. This thesis addresses the problem by making use of Quantity Event Logs to derive key inventory metrics like lead time, demand, and service level. A systematic meta-review and methodical derivation process define the data requirements and computation of these metrics, which are then implemented in the DISQVER web application to enable actionable, data-driven decision-making. Evaluation on real-world QEL data demonstrates that this approach effectively uncovers process inefficiencies and enhances inventory control strategies.

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1 Introduction

The American Production and Inventory Control Society describes inventory management as a field of business management focused on the planning and regulation of stock levels. Its primary objective is to ensure that specific products or items are maintained at an appropriate quantity. Effective inventory management systems should account for the product, the customer, and the processes involved in making the product accessible. While the expenses associated with managing inventory throughout the process are not immediately visible, they ultimately contribute to the overall product cost [1]. Inventory management basically serves two main goals [2]. Primarily, effective inventory management ensures the availability of goods, which is crucial for maintaining smooth operational processes. It is essential to have the necessary materials available in the appropriate quantities, of the required quality, and at the right time to meet a defined service level. A secondary objective is to maintain this service level while minimizing costs. Since it is not feasible to stock all items at any cost, strategic decisions must be made to balance inventory availability and cost efficiency. [3].

Process Mining (PM) is recognized as a valuable tool for analyzing and improving complex processes based on event logs [4]. Nevertheless, the utilisation of PM within the domain of logistics remains limited. [5]. The main reason for this discrepancy lies in the data availability [6]. Logistics processes do not necessarily fulfil all requirements data needed. fortunately the concept of Quantity Event Log (QEL) has been introduced. As an extension of Object-centric Event Log (OCEL) enabling the identification of dependencies between the execution of activities, sub-processes, and item levels without needing identifiers for all items [6]. Current process mining techniques generally operate under two assumptions: (1) that the control flow is determined solely by the current state of identifiable objects, and (2) that activities and object types are the primary entities, represented by uniquely identifiable events and objects in the event log. However, these assumptions do not apply to inventory management processes (IMPs), where the execution of an event can also be influenced by quantities of products that lack unique identifiers (For instance, it is not logical to assign an ID to every paperclip or rubber band.) [6].

In this work, we provide a method for 1) identifying key metrics relevant for inventory management processes, and 2) calculating and visualizing these key metrics. To achieve this, the DISQVER web application is implemented, enabling the application of Object-Centric Process Mining (OCPM) in inventory management. This approach facilitates data-driven decision-making based on the analyses generated by the tool.

Figure 1.1 illustrates the overall methodology and workflow of our approach. The diagram highlights how domain knowledge from the QEL is leveraged to identify key metrics namely, lead time, demand, and service level which are critical for effective inventory management. It further shows that each metric is visualized using customized techniques that enhance understanding and support informed decision-making.

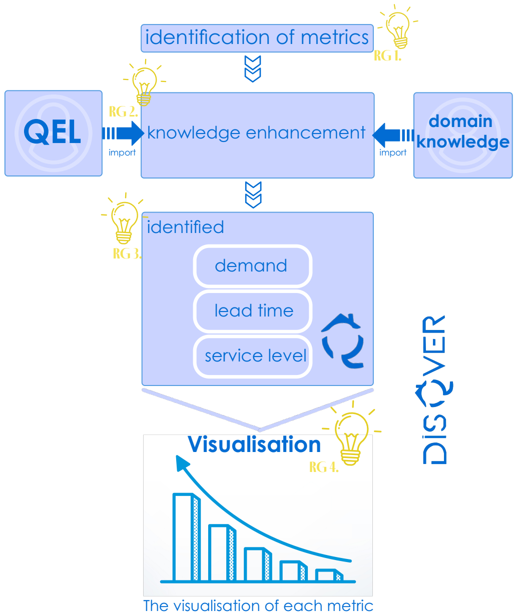


Figure 1.1: Overview of the methodology: integrating QEL domain knowledge, key metric identification (lead time, demand, service level), and targeted visualization to enhance decision-making.

1.1 Motivation

It has been shown that inventory is often the biggest hidden cost in a business. It is unwise to assume that the cost of inventory will be absorbed by any party. Those who do not pass on the cost of inventory risk going out of business. [1]. Therefore, making informed and data-driven decisions in inventory management is critical to maintaining both profitability and operational efficiency. The introduction of the Quantity Event Log addresses a gap by extending existing process mining methods to incorporate quantity-based dependencies. Using QEL, it becomes possible to identify relationships between aggregated counts of items, subprocesses, and activities without requiring unique identifiers for every item. Our proposed method leverages QEL to derive key metrics for inventory management. By visualizing these key metrics, decision-makers gain actionable insights into their inventory processes.

1.2 Problem Statement

muss noch gemacht werden, weil es nicht konkret genug ist

Inventory management in logistics is a complex area that does not fit well with traditional process mining methods. Typical PM techniques struggle to handle things like identifying standard inventory levels or key performance metrics [6]. On top of that, logistics is one of the least explored areas in PM, so there is still a lot we do not know about how to improve these processes [5]. While quantity event logs could help us better understand these processes, they have not been used to their full potential yet. This means we are missing out on opportunities to make smarter, data-driven decisions.

1.3 Research Questions and Goals

To address the problem of improving inventory management in logistics using process mining and Quantity event logs , the work is structured around the following research questions (RQs)

RQ1 What are the key Metrics relevant to inventory management?

RQ2 What information is needed to fully support these Key Metrics, and how should this data be structured in an event log?

RQ3 How can key inventory management metrics be derived from a Quantity Event Log?

RQ4 How can these metrics be effectively visualized to support data-driven decision-making in inventory management?

To answer these research questions, the following research goals (RGs) are defined:

RG1 Identify the key metrics that are critical for effective inventory management in logistics.

RG2 Determine the necessary data requirements and structure for event logs to fully support these key metrics.

RG3 Develop and implement a method to extract and calculate key inventory management metrics from QELs.

RG4 Implement a web application for visualizing key metrics in inventory management.

1.4 Contributions

This thesis makes several contributions to the field of inventory management, addressing both scientific and practical aspects. In achieving the research goals (RG1–RG4), the following contributions have been made:

1. **Scientific Contributions:**

- A systematic meta-review of literature reviews and studies on multi-echelon systems and inventory management. This review identified the key metrics critical for effective inventory management, thereby addressing RQ1.
- A detailed specification of the data requirements and event log structure necessary to support these key metrics. This contribution establishes a solid foundation for structuring QELs to facilitate metric derivation, addressing RQ2.
- A methodological framework for deriving key inventory management metrics from QELs. This framework includes the extraction of demand, lead time, and service level measures, which directly addresses RQ3.

2. **Implementation Contributions:**
   - The development and implementation of the Disqver application, a web-based tool that visualizes key inventory management metrics. This tool supports data-driven decision-making by providing interactive visualizations for demand, lead time, and service level analyses, thereby addressing RQ4.

These contributions advance the theoretical understanding of inventory management by defining key metrics and data structures, while also providing practical tools that can be directly applied in logistics and inventory control settings.

1.5 Thesis Structure

The remainder of this thesis is structured as follows:

- **Chapter 2 Preliminaries**: Presents the fundamental mathematical concepts and background information that underpin the analysis throughout the thesis.
- **Chapter 3 Related Work**: Reviews existing literature on inventory management analysis using process mining.
- **Chapter 4 Key Metrics Identification**: Identifies and discusses the critical metrics for effective inventory management.
- **Chapter 5 Derivation of Relevant Metrics from a QEL**: Describes the methodology for extracting and calculating key inventory management metrics from Quantity Event Logs.
- **Chapter 6 Implementation**: Details the design and development of the Disqver application, a web-based tool for visualizing the computed metrics.
- **Chapter 7 Evaluation**: Presents an evaluation of both the derived metrics and the Disqver application.
- **Chapter 8 Discussion**: Discusses the implications, limitations, and potential improvements of the proposed methods and application.

- **Chapter 9 Conclusion**: Summarizes the contributions of the thesis and outlines directions for future research.

2 Preliminaries

In this chapter, we introduce terms and concepts from both domains, object-centric process mining and inventory management, which we refer to in the remaining work.

2.1 Mathematical Foundations

I. $\mathbb{N} = \{1, 2, 3, \dots\}$ denotes the set of *natural numbers*, $\mathbb{N}_0 = \mathbb{N} \cup \{0\}$ the set of *natural numbers including zero*, $\mathbb{Z}$ the set of *integers* and $\mathbb{R}$ the set of *real numbers. Infinity* is denoted by ∞ and is not contained in any of the aforementioned sets.

II. For a set X, $\mathcal{P}(X)$ denotes the *powerset* of X, i.e., the set of subsets of X. And $\mathcal{B}(X)$ the set of all multisets over X. A multiset is an ordered pair (X, m) where X is a set and m is a function that assigns to each element of X a non-negative integer, called its *multiplicity.* For example, let $X = \{a, b, c\}$ and $y : X \to \mathbb{N}_0$ assigns a natural number to every element of a set, then $y_1 = [a^2]$ and $y_2 = [a, b^3]$ are multisets of X and $y_1, y_2 \in \mathcal{B}(X)$

III. A *total function* $f\colon X \to Y$ assigns a value $f(x) \in Y$ to each $x \in X$. A *partial function* $f\colon X \not\to Y$ does not necessarily map all $x \in X$ to a value in Y. For those $x \in X$ where $f(x)$ is undefined, we write $f(x) = \perp$.

For a function or partial function $f\colon X \to Y$, the *range* of f is given by $\mathrm{rng}(f) = \{f(x) \mid x \in X\} \setminus \{\perp\}$. The *domain* of f is denoted by $\mathrm{dom}(f) = \{x \in X \mid f(y) \neq \perp\}$.

2.2 Object-Centric Event Logs

in this section, we introduce the concept of object-centric event logs (OCEL) as well as the concept of quantity event logs (QEL) which are an extension to an OCEL and will be used to identify inventory management metrics.

To define object-centric event logs and quantity event logs, we first need to give some preliminary definitions:

Definition 2.2.1. (Universes). Let $\mathbb{U}_\Sigma$ be the universe of of strings. The following universes are defined as pairwise disjoint sets:

- $\mathbb{U}_{ev} \subseteq \mathbb{U}_\Sigma$ is the universe of events,
- $\mathbb{U}_{etype} \subseteq \mathbb{U}_\Sigma$ is the universe of event types,

- $\mathbb{U}_{obj} \subseteq \mathbb{U}_{\Sigma}$ is the universe of objects,
- $\mathbb{U}_{otype} \subseteq \mathbb{U}_{\Sigma}$ is the universe of object types,
- $\mathbb{U}_{attr} \subseteq \mathbb{U}_{\Sigma}$ is the universe of attribute names,
- $\mathbb{U}_{val} \subseteq \mathbb{U}_{\Sigma}$ is the universe of attribute values,
- $\mathbb{U}_{time} \subseteq \mathbb{U}_{\Sigma}$ is the universe of timestamps, including $0, \infty \in \mathbb{U}_{time}$, totally ordered with $0 \leq t \leq \infty$ for all $t \in \mathbb{U}_{time}$.
- $\mathbb{U}_{qual} \subseteq \mathbb{U}_{\Sigma}$ is the universe of qualifiers.
- $\mathbb{U}_{it} \subseteq \mathbb{U}_{\Sigma}$ is the universe of item types.
- $\mathbb{U}_{cp} \subseteq \mathbb{U}_{\Sigma}$ is the universe of Collection points.

Definition 2.2.2 (Counter, Item quantity)**.** A counter is a function that maps each item type to an item quantity $c : I \to \mathbb{Z}$ where I is the set of item types $I \subseteq \mathbb{U}_{it}$. For any two counters c_1, c_2, the sum of the counters $c_1 \oplus c_2$ is defined as $(c_1 \oplus c_2)(it) = c_1(it) + c_2(it)$. For example let $I = \{x, y, z\}$, c_2 =$[x, y^{-2}, z^3]$ and $c_3 = [x^2, y]$ then:
$c_2 \oplus c_3 = c_1(it) + c_2(it) = [x^3, y^{-1}, z^3]$

Definition 2.2.3 (Collection Counter)**.** A collection counter is a function that maps each collection point to a counter $cc : CP \to \mathcal{P}(I)$ and $C(CP, I) = CP \to \mathcal{I}(I)$ where CP is the set of collection points $CP \subseteq \mathbb{U}_{cp}$ and $\mathcal{P}I$ is the set of all possible counters ocer I. For any two collection counters cc_1, cc_2, the sum of the collection counters $cc_1 \oplus cc_2$ is defined as $(cc_1 \oplus cc_2)(cp) = cc_1(cp) \oplus cc_2(cp)$. For example let $CP = \{a, b, c\}$, cc_1 =$(cp_1$,$[a, b^{-2}, c^3])$ and $cc_2 = (cp_1$,$[a^2, b])$ then:
$cc_1 \oplus cc_2 = cc_1(cp_1) + cc_2(cp_1) = [a^3, b^{-1}, c^3]$

Based on these preliminary definitions, we can now define an OCEL and a QEL:

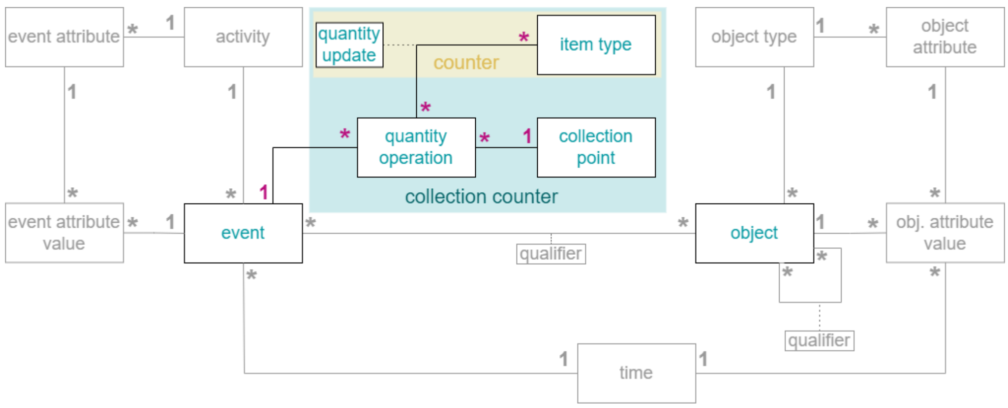


Figure 2.1: OCEL and QEL Metamodel[6]

Definition 2.2.4 (Object-Centric Event Log)**.** An Object-Centric Event Log (OCEL) is a tuple

$$L = (E, O, EA, OA, \mathit{evtype}, \mathit{time}, \mathit{objtype}, \mathit{eatype}, \mathit{oatype}, \mathit{eaval}, \mathit{oaval}, \mathit{E2O}, \mathit{O2O})$$

where

- $E \subseteq \mathbb{U}_{ev}$ is the set of events,
- $O \subseteq \mathbb{U}_{obj}$ is the set of objects,
- $\mathit{evtype}\colon E \to \mathbb{U}_{etype}$ assigns event types to events,
- $\mathit{time}\colon E \to \mathbb{U}_{time}$ assigns timestamps to events,
- $\mathit{objtype}\colon O \to \mathbb{U}_{otype}$ assigns object types to objects,
- $EA \subseteq \mathbb{U}_{attr}$ is the set of event attributes,
- $OA \subseteq \mathbb{U}_{attr}$ is the set of object attributes,
- $\mathit{eatype}\colon EA \to \mathbb{U}_{etype}$ assigns event types to event attributes,
- $\mathit{oatype}\colon OA \to \mathbb{U}_{otype}$ assigns object types to object attributes,
- $\mathit{eaval}\colon (E{\times}EA) \not\to \mathbb{U}_{val}$ assigns values to event attributes,
- $\mathit{oaval}\colon (O{\times}OA{\times}\mathbb{U}_{time}) \not\to \mathbb{U}_{val}$ assigns values to object attributes,
- $\mathit{E2O} \subseteq E{\times}\mathbb{U}_{qual}{\times}O$ are the qualified event-to-object relations,
- $\mathit{O2O} \subseteq O{\times}\mathbb{U}_{qual}{\times}O$ are the qualified object-to-object relations.

Definition 2.2.5 (Quantity Event Log)**.** A Quantity Event Log (QEL) is a tuple

$$QEL = (OCEL, I, CP, eqty, \prec_e)$$

where

- $OCEL$ is an OCEL,
- $I \subseteq \mathbb{U}_{it}$ is the set of item types,
- $CP \subseteq \mathbb{U}_{cp}$ is the set of collection points,
- $\mathit{eqty} : E \to C(CP, I)$ a mapping of events to quantity operations for all collection points,
- $\prec_e \subseteq (E{\times}E)$ is a total order on events.

Definition 2.2.6 (Quantity Net)**.** A Quantity Net is a tuple

$$QN = (OCPN, CP, QA)$$

where

- $OCPN$ is a Object-Centric Petri Net,
- CP is a set of collection points,
- QA is a set of undirected arcs between collection points and events.

Definition 2.2.7 (Quantity State)**.** Consider a quantity event log $QEL = (OCEL, I, CP, eqty, \prec_e)$, which corresponds to a set of events $E \subseteq \mathbb{U}_{ev}$. The function $qstate : E \rightarrow C(CP, I)$ represents the quantity state at the moment an event $e \in E$ occurs:

$$qstate(e) = \bigoplus \{eqty(\blacktriangleright)\} \uplus \{eqty(e') \mid e' \prec_e e\}$$

In other words, the quantity state following an event's execution is obtained by incorporating the event's quantity operation:

$$post(qstate(e)) = qstate(e) \oplus eqty(e).$$

Furthermore, the quantity state at a specific collection point ($cp \in CP$) at the moment of an event ($e \in E$) is referred to as its *item level*, denoted as ($ilvl^{cp}(e) \in \mathcal{P}I$).

2.3 Inventory Management performance indicators (Metrics)

In this section, we introduce the concept of inventory management performance indicators, which are used to evaluate the performance of inventory management processes. Logistics performance is typically assessed using both quantitative (hard) and qualitative (soft) metrics. Quantitative metrics focus on measurable factors such as order cycle time, fill rates, and costs. In contrast, qualitative metrics capture aspects like managerial assessments of customer satisfaction and loyalty. While quantitative indicators can be calculated using straightforward mathematical formulas, evaluating qualitative metrics often requires more advanced analytical techniques.[7]

3 Related Work

This chapter discusses related work in the field that combines process mining and inventory and logistics management.

Kretzschmann et al.[8] introduce an OCDM to integrate and standardize data from multiple information systems (e.g., demand forecasting, ERP systems, and document metadata sources). This model abstracts the complexity inherent in traditional inventory processes (Order-to-Cash and Purchase-to-Pay) and forms a unified view of the data. From this integrated data, a single object-centric event log (OCEL A) is extracted.
The initial event log is enriched with key inventory-related metrics such as Economic Order Quantity, Reorder Point, Safety Stock, Maximum Stock, and Overstock. This enrichment results in a more informative log (OCEL B) that allows for an event-driven analysis of process behaviors and inefficiencies.
With (OCEL B) in hand, the authors apply process mining techniques to systematically analyze process behaviors. This analysis focuses on identifying root causes for common inventory issues like understock and overstock, which are critical in optimizing overall inventory management.

Terlouw[9] propose a hybrid methodology that first applies conventional process mining techniques to uncover the underlying structure of logistics processes. The initial discovery using the inductive mining algorithm provides insights into activity frequencies, dependencies, and timing aspects.
The approach further incorporates principles from Lean Six Sigma to determine optimal inventory levels. Using a continuous review model, the authors calculate the inventory reorder point and the optimal order quantity thereby bridging process mining insights with practical inventory control.

In [10] the Open Trip Model (OTM) (an open-source data sharing standard used in logistics) to overcome challenges related to interoperability, data loss, and quality when aggregating event data from diverse systems. They argue that by mapping the OTM data model to a generic event log structure (Not an OCEL), the minimum requirements for process mining can be satisfied.
After creating an event log from the mapped data, the authors use the process mining tool Disco to import the log, generate a process model, and extract performance metrics (e.g., activity frequencies, process variants, and durations). This step demonstrates that the OTM can serve as a viable foundation for building process mining applications in the logistics domain.

Knoll et al.[11] address the limitations of traditional, pen-and-paper value stream mapping (VSM) in complex, dynamic manufacturing environments. They propose a novel methodology that combines multidimensional process mining (MDPM) with established lean production principles and VSM to support continuous improvement in internal logistics for mixed-model assembly lines.
After automatically mapping raw transfer orders from the warehouse management system to physical logistics activities, the orders are trasformed into a standardized event logs. The authors then apply MDPM to analyze the logs, by first discovering a process models to analysis the current state maps created via VSM. then a preformance analysis is conducted calculating preformance metrics and lastly a conformance analysis is done.

4 Key Metrics Identification

In this chapter, we identify the key metrics and domain knowledge necessary to address inventory management challenges in logistics. To answer RQ1 (What are the key Metrics relevant to inventory management?) and RQ2 (What information is needed to fully support these Key Metrics, and how should this data be structured in an event log?), we conducted a meta-review on a set of literature reviews and some Studies focusing on the themes of multi-echelon systems and inventory management. This chapter summarizes the findings from these studies, highlights their similarities, and derives the essential knowledge needed.

4.1 Search Method

To identify the key metrics and domain knowledge necessary for addressing inventory management challenges, a systematic literature search was conducted.

A meta-review was performed on existing literature reviews and studies focusing on multi-echelon systems and inventory management in logistics. This search aimed to capture a broad spectrum of perspectives and methodologies. The following academic databases were used:

- Scopus
- Web of Science
- Google Scholar

A combination of keywords was employed, including:

- *"inventory management"*,
- *"multi-echelon inventory models"*,
- *"performance measurement in logistics"* and,
- *"warehouse performance"*.

This search allowed us to identify:

- Performance metrics commonly used in logistics,
- The components of existing inventory management systems,

- Key performance indicators used to evaluate these systems, and
- The data needed to support these metrics.

which is exactly the objective of our search.

4.2 Overview of the Reviewed Literature

Warehouse performance measurement: a literature review

This literature review examines how warehouses are assessed in terms of operational performance. As supply chains grow increasingly complex, warehouse managers face the challenge of selecting appropriate performance metrics—such as those related to time, cost, quality, and productivity—given the absence of a universally accepted set of measures. This review addresses this issue by systematically analyzing prior research and identifying key metrics commonly used in warehouse evaluations. The authors synthesized a gruppe of performance metrics from a selection of studies. These metrics were categorized into two main groups: direct indicators, which measure concrete outcomes such as processing speed or order accuracy, and indirect indicators, which influence performance more broadly, such as resource utilization. Additionally, the study introduces a framework that delineates the scope of these indicators, clarifying their definitions and their relevance to various aspects of warehouse operations. Overall, the findings reveal a wide range of performance metrics used in the literature, yet no clear consensus on which are most effective, posing a challenge for managers in selecting the most suitable measures[7].

A Typology and Literature Review on Stochastic Multi-Echelon Inventory Models

This literature review looked into the development of stochastic multi-echelon inventory models, a field that has been evolving for more than 50 years. this field is examined in this review of the literature. From early theoretical models to more useful optimization techniques applied in actual supply chains, it identifies important research aspects. Additionally, it lists the kinds of metercs that have been studied along with their primary accomplishments. The authors used a systematic approach to organize the review. They started by compiling citations from important review papers and handbooks[12].

A comprehensive survey of guaranteed-service models for multi-echelon inventory optimization

Here is the guaranteed-service models (GSM) is being explored for optimizing multi-echelon inventory systems. Although multi-echelon inventory management has been widely researched, much of the focus has been on stochastic-service models (SSM), creating a noticeable gap in the literature regarding GSM. this paper addresses that gap by giving a thorough overview of existing GSM models, the performance maguaris they use and the methods used to solve them. To put this review together, the authors carried out a systematic search across databases like Web of Science, Google Scholar, and ScienceDirect[13].

A Review and Reflection on Inventory Management of Perishable Products in a Singleechelon Model

This paper dives into managing inventory for perishable goods, particularly using single-echelon continuous review models. It makes the point that conventional inventory models, which frequently depend on profit or total cost measures, don't necessarily capture the complexity of supply chains in the real world, particularly when maximizing system performance is the aim. The study recommends switching to a multi-metric strategy that takes into account more variables than only financial ones. In today's dynamic and fast-paced business environment, it argues for a more complete approach to managing perishable inventory by examining the limitations of single-metric solutions[14].

Logistics-oriented inventory analysis

The paper explores how modern businesses can optimize their inventory management to meet increasingly demanding customer expectations while keeping costs under control. The authors present the idea of inventory operating curves as a useful analytical tool because they understand that success nowadays depends not only on operational effectiveness and product quality but also on important logistical metrics like lead time, service level, and delivery reliability. Businesses can use these curves to calculate the optimal inventory levels required to meet service performance goals. Even companies without complex IT infrastructures can utilize the strategy because it makes use of data that is normally available from ordinary ERP or warehouse management systems[15].

Performance Measurement on Inventory Management and Logistics Through Various Forecasting Techniques

This study looks into how manufacturing efficiency can be increased through effective inventory management and logistics assessment. In order to handle stochastic demand and avoid stock-outs, it uses a variety of forecasting approaches in addition to economic order amount, reorder point, and safety stock calculations. It also uses an advanced categorization system to categorize inventory products into fast, slow, and non-moving groups. Furthermore, it assesses logistics performance, particularly on-time delivery and truck capacity utilization, and discovers that vehicles are running at slightly more than 50% of their potential. Recommendations for maintaining suitable safety stocks and enhancing packing techniques are included in the paper's conclusion to improve supply chain performance overall[16].

The studies in this section addressed a range of inventory management systems across various industries and modeling approaches. By synthesizing their findings, we identified key common metrics that are consistently relevant across different inventory models. These shared aspects directly answer RG1, as they provide a structured understanding of the most critical metrics in inventory management.

Furthermore, since the reviewed papers also discuss how these metrics are measured, tracked, and applied in decision-making, their insights help define the necessary data structures and event log attributes needed to support these metrics. This directly contributes to answering RG2, ensuring that the event log aligns with real-world inventory management requirements.

4.3 Findings from the Literature

In this section, we summarize the findings from the literature regarding key inventory management metrics. The analysis is based on several studies, and the results are organized into two tables. The table 4.1 provides an overview on which metrics are covered in each study, while the table 4.2 lists the key metrics identified in the literature as well as an explantion and the necessary data to support them.

Table 4.1: Overview of Literature Findings on Key Inventory Management Metrics. **Legend:** Green cells indicate that the literature source addresses the corresponding metric; red cells indicate that the metric is not covered.

		Metrics															
		E[1]	S[2]	ToA[3]	I[4]	C[5]	LT[6]	D[7]	RtS[8]	RP[9]	LS[10]	SR[11]	IC[12]	TP[13]	TO[14]	FR[15]	RP[16]
Literature	[7]	red	red	red	red	green	green	green	green	green	red	green	green	green	green	green	green
	[12]	green	green	green	green	green	green	green	green	green	green	green	green	red	red	red	red
	[13]	green	red	red	red	green	green	green	red	green	red	green	red	red	red	red	red
	[14]	green	green	red	red	red	green	green	green	green	red	green	red	red	red	green	red
	[15]	red	red	red	red	red	green	green	red	red	green	green	red	green	red	green	red
	[16]	red	red	red	red	green	green	green	red	red	red	green	green	red	green	red	green

E = Echelons, 2) S = Structure, 3) ToA = Timing of Activities, 4) I = Information, 5) C = Capacity, 6) LT = Lead Time, 7) D = Demand, 8) RtS = Reactions to Stockout, 9) RP = Replenishment Policy, 10) LS = Lot Size, 11) SR = Service Requirements, 12) IC = Inventory Cost, 13) TP = Throughput, 14) TO = Turnover, 15) FR = Fill Rate, 16) RP = Reorder Point.

4.4 Common Insights and Derivation of Necessary Domain Knowledge

The literature review reveals three particularly important commonalities that are frequently discussed in the studies examined:

Lead Time

Delivery time plays a crucial role in the efficiency and reliability of an inventory management system. Reducing delivery times can have a direct impact on inventory levels and service quality. this metric is associated with ether an order or item and whether it is a costumer oder or an replenishment order. the lead time can be also associated with a supplier for the replenishment and a retailer or costumer for the costumer order. based on that we need to know when the order was placed/registered in the system to which supplier / retailer the and when did it arrive. so if we look at it from a log perspective, the log need to have placed/registered and arrival activity. Costumer order and replenishment order need to be distinguishable object and have information on the retailer respectively supplier for example as an attribute.

Demand

Demand is one of the key drivers of inventory management. It varies by market and product and must therefore be carefully analyzed and forecasted to ensure optimal inventory levels. each item has its own demand so to determine the demand the costumer order need to have the information which item is being bought. so from a log perspective the costumer order object need to have the items information (how many items and the quantity of each item) since the costumer order also has the retailer/costumer information the demand can be also determine for each retailer/costumer.

Service Requirements

Service requirements, such as cost requirements or service levels, are critical for aligning inventory management with business objectives. focusing on the service levels, we need to know fulfillment of costumer orders, so again we need to know the quantity ordered and the quantity arrived.

These three aspects are crucial for the design of efficient inventory management systems and should be given special consideration in any further analysis.

4.5 Summary

This chapter analyzed key inventory management metrics derived from multi-echelon inventory literature. The findings highlight three fundamental aspects *lead time, demand, and service requirements* which are essential for effective inventory control. So in the next chapter we will take a closer look on RQ3 (How can key inventory management metrics be derived from a QEL?).

Table 4.2: Key Inventory Management Metrics Identified in the Literature

Key Metric	**Explanation**	**Necessary Data**
Echelons	Number of echelons in the supply chain	
Structure	Type of structure (Serial, Convergent, Divergent, etc.)	
Timing of activities	Actions possible at any or at specific points in time	
Information	Source and level of available information	
Capacity	Finite and infinite storage capacity	
Lead time	Time it takes to deliver an item/order	Timestamps for order placement and delivery
Demand	Demand for an item (Deterministic, Stochastic, Normal, Poisson, etc.)	The Quantity of each customer order
Reactions to stockout	System responses when stock is depleted (Backordering, Guaranteed service, Lost sales)	Order Quantities, the canceled orders as well as the orders with multibel deleverys and there timestamps
Replenishment policy	How the stock is being restocked (Base stock, (s, S), (s, S, Q), etc.)	Reorder point, reorder quantities, safty stock and stock limit
Lot size	Release quantity (Flexible/Fixed)	The quantity of each replenishment
Service requirements	Objectives achieved via control policies	Placement quantities as well as arrival quantities
Inventory Cost	Total storage and handling costs	Storage cost
Throughput	Graphical representation of an item's inventory history over time	Inventory input, output as well as the demand and inventory level
Turnover ratio	Ratio between sold goods and average inventory	customer order quantity and cost per item and the average inventory level
Fill rate	Proportion of orders fulfilled on the first shipment	Orders that did not split in to multibel deleverys and the total orders
Reorder Point	Stock level that triggers a new order	Demand data, reorder trigger events

5 Derivation of Relevant Metrics from a QEL

After identifying the relevant metrics in the previous chapter, we introduce methods for their determination in this chapter. By doing so, we provide an answer to the third research question (RQ3) and reach research goal (RG3). We will first limit our scope to a subset of metrics as seen in the previous chapter, before considering the overall data required for their identification using a QEL. For each of these metrics we will provide the following:

- A definition of each of these metrics in the context of a QEL.
- A consideration of the additional information required for this metric in particular and the requirements on the event log they pose.
- A method to determine the measure using a QEL and the additionally provided domain knowledge.
- An example of the metric's determination using the example QEL.

Before providing the methods for the determination of these metrics, we will first introduce an example QEL and the data it contains, to provide a basis for the following sections and make the methods more understandable.

5.1 Example QEL

We present a simple process, illustrated in Figure 5.1, to demonstrate the concept of a QEL. The process involves two object types Ingredient-delivery and Pizza-order and seven events: Register Incoming Ingredients, Check the Quality, Accept and Add to Inventory, Do Not Accept and Send Back, Register Pizza, Prepare Pizza, and Send Pizza. Additionally, there are two collection points: Planning and Physical.

Consider a small pizza store that purchases ingredients and sells pizzas. Whenever ingredients are needed, a replenishment order is placed. Upon arrival, the ingredients undergo a quality check. If they meet the required standards, they are accepted and added to inventory; otherwise, they are rejected and returned. When a customer places an order, the store registers the order, prepares the pizza, and then delivers it to the customer.

Table 5.1: Event, Object, and Quantity Operations Data

Table 5.2: Data from Event

ocel_id	ocel_type
ev_1	Register Incoming Ingredients
ev_2	Register Incoming Ingredients
ev_3	Check the quality
ev_4	Check the quality
ev_5	Accept and add to inventory
ev_6	Do not accept and send back
ev_7	Register pizza
ev_8	Register pizza
ev_9	Prepare pizza
ev_10	Prepare pizza
ev_11	Send pizza
ev_12	Send pizza
ev_13	Register pizza
ev_14	Register pizza
ev_15	Prepare pizza
ev_16	Prepare pizza
ev_17	Send pizza
ev_18	Send pizza

Table 5.3: Data from Object

ocel_id	ocel_type
o_1	Ingredient-delivery
o_2	Ingredient-delivery
o_3	Pizza-order
o_4	Pizza-order
o_5	Pizza-order
o_6	Pizza-order

Table 5.4: Data from Quantity Operations

ocel_id	ocel_cpid	Dough	Tomato_sauce	Cheese
init	planning	None	None	None
init	physical	10	10	10
ev_1	planning	10	10	10
ev_2	planning	5	5	5
ev_5	physical	10	10	10
ev_11	physical	-1	-2	-3
ev_11	planning	-1	-2	-3
ev_12	physical	-1	-2	-3
ev_12	planning	-1	-2	-3
ev_17	physical	-3	-7	-6
ev_17	planning	-3	-7	-6
ev_18	physical	-2	-3	-3
ev_18	planning	-2	-3	-3

Table 5.5: Event Time Data

Table 5.6: Register Incoming Ingredients

ocel_id	ocel_time
ev_1	2025-01-01 00:00:01
ev_2	2025-01-01 00:00:10

Table 5.7: Check the Quality

ocel_id	ocel_time
ev_3	2025-01-01 00:00:03
ev_4	2025-01-01 00:00:14

Table 5.8: Accept and Add to Inventory

ocel_id	ocel_time
ev_5	2025-01-01 00:00:05

Table 5.9: Do Not Accept and Send Back

ocel_id	ocel_time
ev_6	2025-01-01 00:00:16

Table 5.10: Register Pizza

ocel_id	ocel_time
ev_7	2025-01-01 00:00:07
ev_8	2025-01-01 00:00:18
ev_13	2025-02-01 00:00:07
ev_14	2025-03-01 00:00:18

Table 5.11: Prepare Pizza

ocel_id	ocel_time
ev_9	2025-01-01 00:00:09
ev_10	2025-01-01 00:00:20
ev_15	2025-02-01 00:00:09
ev_16	2025-03-01 00:00:20

Table 5.12: Send Pizza

ocel_id	ocel_time
ev_11	2025-01-01 00:00:11
ev_12	2025-01-01 00:00:22
ev_17	2025-02-01 00:00:11
ev_18	2025-03-01 00:00:22

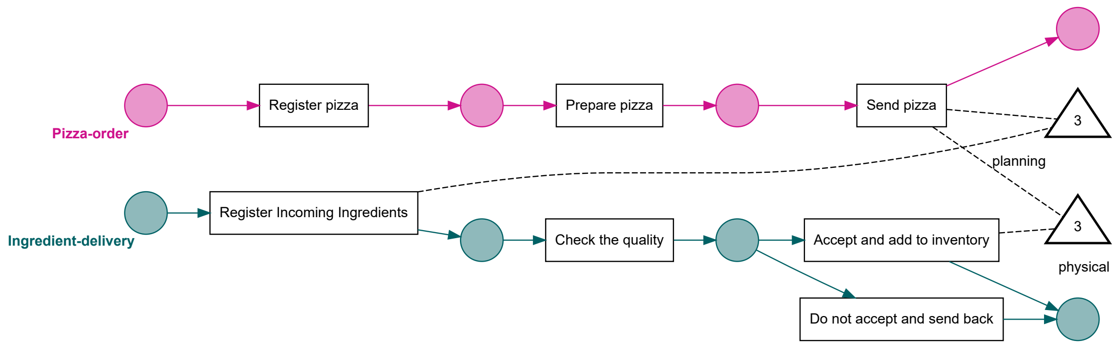


Figure 5.1: Example Quantity Event Log

The quantity net in Figure 5.1 was discovered from the QEL data that are prensented in Table 5.1 and 5.5.

Due to the large number of metrics identified above, we selected the most relevant ones as part of this thesis' scope:

- Lead Time
- Demand
- Service Level

Considering these measures, we quickly realize that a QEL alone is not sufficient for their determination. Additional information is required regarding both the involved object types and the executed activities.

For all these measures, it is essential to know which object type represents an order, denoted as $OT^o \in \mathbb{U}_{ordertype}$. Additionally, to determine the **lead time**, we must specify which activities correspond to the placement and arrival of an order, denoted as $a^{pl}, a^{arr} \in A$.

For **demand**, we need to know the relevant item types and the collection point where the items are stored. These form a subset of the items from the QEL, which we denote as $I^{\text{demand}} \subseteq I$ and $CP^{\text{demand}} \subseteq CP$.

Similarly, for **service level assessment**, in addition to the order type, we must know the planning collection point of the order and the physical item level at the time of order placement. Thus, both the physical and planning collection points are required, denoted as $CP^{\text{planning}} \subseteq CP$ and $CP^{\text{physical}} \subseteq CP$. Furthermore, we will use the *item level* function as defined in 2.2.7.

In the following sections, we present methods for deriving these measures using a QEL and the additional information provided.

5.2 Demand

As we saw in chapter 4 calculting the demand and forcetion it is a very crucial task. Hier we provide a way to only derive it from the QEL. The demand will be presented in a monthly granetuty. To do so wen need to be able to identify the 1) set of itemes that the demand will be calculated for, and 2) in which collection point they are. Using this infrmation we can now for each order sum the *eqty* in a monthly granetuty of all arrival events.

Definition 5.2.1 (Demand Calculation)**.** Let $QEL = (OCEL, I, CP, eqty, \prec_e)$ be a quantity event log, and let $I^{\text{demand}} \subseteq I$ be the set of items relevant for demand calculation, and $CP^{\text{demand}} \subseteq CP$ the corresponding collection points. The demand for an item $i \in I^{\text{demand}}$ at collection point $cp \in CP^{\text{demand}}$ during month m is given by:

$$d(i, cp, m) = \sum_{e \in E_m} eqty(e)(cp, i)$$

where E_m is the set of events occurring in month m.

In this approach, we consider only arrival events contributing to the inventory levels at specific collection points. This ensures that the demand is derived from actual recorded movements within the QEL.

Example 1 (Demand Determination from QEL)*.* Given the QEL in Tables 5.1 and 5.5, we now calculate the monthly demand for pizza items at the planning collection point.

For this example, assume the following:

- The relevant object type for demand calculation is **Pizza**, so the items for which we calculate the demand are $I^{\text{demand}} = \{Dough, Tomato\_sauce, Cheese\}$. in this exsample we only consider the $Tomato\_sauce$ item.
- The collection point for demand is the *planning* collection point.
- The demand is calculated based on arrival events, which in this case are the events with ocel_type `Send pizza`.

From Table 5.5, we extract the following relevant events for `Send pizza`:

- **January 2025**:
  - Event `ev_11` at `2025-01-01 00:00:11`

- Event `ev_12` at `2025-01-01 00:00:22`
- Quantity Operations: $eqty(ev\_11)(planning, Tomato\_sauce) = -2$ and $eqty(ev\_12)(planning, \text{Pizza}) = -2$.

- **February 2025**:
  - Event `ev_17` at `2025-02-01 00:00:11`
  - Quantity Operation: $eqty(ev\_17)(planning, Tomato\_sauce) = -7$.

- **March 2025**:
  - Event `ev_18` at `2025-03-01 00:00:22`
  - Quantity Operation: $eqty(ev\_18)(planning, Tomato\_sauce) = -3$.

Thus, the monthly demand for pizzas at the planning collection point is computed as:

$$\begin{aligned} d(Tomato\_sauce, planning, \text{Jan 2025}) &= (-2) + (-2) = -4, \\ d(Tomato\_sauce, planning, \text{Feb 2025}) &= -7, \\ d(Tomato\_sauce, planning, \text{Mar 2025}) &= -3. \end{aligned}$$

In this context, a negative demand indicates that tomato sauce have been consumed, reducing the inventory. This example demonstrates how the QEL can be used to derive monthly demand for pizza items at a specified collection point.

5.3 Lead Time

One of the most important measures according to our review is the Lead Time. For every object $o \in O$ of the type order $type(o) = ot^{order}$, we need to be able to identify 1) the event of placing this order, and 2) the event describing the order's arrival. Using these events, we can determine the lead time by determining the timedelta between these event's timestamps.

Definition 5.3.1 (Lead Time Detection)**.** Let $QEL = (OCEL, I, CP, eqty, \prec_e)$ be a quantity event log and $O^o = \{oo \in O \mid type(o) = ot^o\}$ the set of orders. Given the two functions $pl : O^{order} \to E \cup \{\emptyset\}$ and $arr : O^o \to E \cup \{\emptyset\}$ which associate every order with one or none placement and arrival events, the lead time for any order $o^{order} \in O^{order}$ is:

$$lt(o^o) = \begin{cases} tm(arr(o^o)) - tm(pl(o^o)) & \text{if } arr(o^{order}) \neq \emptyset \text{ and } pl(o^o) \neq \emptyset \\ \perp & \text{else.} \end{cases}$$

In the following, we propose the identification of every order's placement and arrival event using the following understanding of the process (and the corresponding data):

- An order is placed by executing an activity $a^{pl} \in A$ describing the placement of an order.

- An order arrives when a corresponding activity $a^{arr} \in A$ is executed.

Even with this understanding, the identification of an object's placement and arrival event's can be challenging. There are multiple possibilities, each entailing different requirements to the data, to determine every object's placement and arrival event.

In this work, we assign single placement and arrival events to orders, by requiring that every order is involved in exactly one event of each activity.

Definition 5.3.2 (Order Placement/Arrival Events)**.** Let $QEL = (OCEL, I, CP, eqty, \prec_e$) be a quantity event log, $O^o = \{oo \in O \mid type(o) = ot^o\}$ the set of orders. For every order $o^{order} \in O^{order}$:

- $\exists e \in E$: $act(e) = a^{pl} \wedge (e, q, o^o) \in E2O \wedge$
- $\nexists e' \in E$ with $e' \neq e \wedge$
- $act(e') = a^{pl} \wedge$
- $(e', q, o^o) \implies pl(o^o) = e$

If no single such event exists, the placement event is empty $pl(o^o) = \emptyset$. Equivalently, for every order $o^{order} \in O^{order}$:

- $\exists e \in E$: $act(e) = a^{arr} \wedge (e, q, o^o) \in E2O \wedge$
- $\nexists e' \in E$ with $e' \neq e \wedge$
- $act(e') = a^{arr} \wedge$
- $(e', q, o^o) \implies arr(o^o) = e$

and $arr(o^o) = \emptyset$ if no single corresponding event can be found in E.

We will now demonstrate the determination of the lead time for the example QEL in Section 5.1.

Example 2 (Lead Time Determination)*.* Given the QEL in Section 5.1, we can determine the lead time for every order $o^{order} \in O^{order}$ by identifying the placement and arrival events for each order. Let $O^{order} = \{o\_3, o\_4, o\_5, o\_6\}$ be the set of orders which are the pizza that we sold in the example. For every order $o^{order} \in O^{order}$, the placement events would be as prensented in table 5.13, and the arrival events would be as prensented in table 5.14. Using the placement and arrival events, we can determine the lead time for every order $o^{order} \in O^{order}$ as follows: The lead time for every order $o^{order} \in O^{order}$ is as presented in Table 5.15.

Table 5.13: Order Placement Events

o^{order}	$pl(o^{order})$
o_3	ev_7
o_4	ev_8
o_5	ev_13
o_6	ev_14

Table 5.14: Order Arrival Events

o^{order}	$arr(o^{order})$
o_3	ev_{11}
o_4	ev_{12}
o_5	ev_{17}
o_6	ev_{18}

Table 5.15: Lead Time for Orders

o^{order}	$lt(o^{order})$	lead time (min)
o_3	$tm(ev_{11}) - tm(ev_7)$	25
o_4	$tm(ev_{12}) - tm(ev_8)$	30
o_5	$tm(ev_{17}) - tm(ev_{13})$	20
o_6	$tm(ev_{18}) - tm(ev_{14})$	40

5.4 Service Level

One of the main goals of inventory management is to serve the customer [1]. Therefore, observing and monitoring service levels is crucial. Bad service levels can lead to customer loss and, consequently, a decline in sales [17]. Studies indicate a strong correlation between retail service levels and customer satisfaction [17].
Two types of service levels are considered:

- **Alpha Service Level** (α): Defined as the probability that incoming demand can be fully met from the physical inventory available at the time of its arrival [18].
- **Beta Service Level** (β): Represents the percentage of demand that can be immediately satisfied from stock on hand [19].

Alpha Service Level Calculation

To calculate the alpha service level, we analyze all orders and determine whether the quantity recorded at the order placement event is equal to the quantity recorded at the order arrival event. Formally, let O^{order} denote the set of orders, and let $pl(o)$ and $arr(o)$ be the placement and arrival events associated with order o, respectively. Then, the alpha service level is given by:

$$\alpha = 1 - \frac{|\{\, o \in O^{order} : eqty(pl(o)) \neq eqty(arr(o))\}|}{|O^{order}|}.$$

In other words, α represents the fraction of orders that are fully satisfied (i.e., for which $eqty(pl(o)) = eqty(arr(o))$).

Beta Service Level Calculation

The beta service level is computed at the item level. For each item $i \in I$, let:

- $q_{bought}(i)$ be the total quantity recorded during order placement for item i, and
- $q_{arr}(i)$ be the total quantity recorded at order arrival for item i (i.e., the current item level).

The fulfillment ratio for item i is then defined as:

$$\beta_i = \frac{q_{arr}(i)}{q_{bought}(i)}.$$

The overall beta service level is computed as the average fulfillment ratio over all items:

$$\beta = \frac{1}{|I|} \sum_{i \in I} \beta_i.$$

Example 3 (Service Level Determination)*.* Consider a simplified scenario extracted from the QEL:

- **Order o_1:**
  - Bought quantities (recorded at placement): 2 units of item A and 3 units of item B.
  - Recorded item levels at arrival: 1 unit of item A and 3 units of item B.
- **Order o_2:**
  - Bought quantities: 2 units of item A and 3 units of item B.
  - Recorded item levels at arrival: 2 units of item A and 3 units of item B.

For the **alpha service level**, we observe:

- Order o_1 is not fully satisfied since $eqty(pl(o_1)) \neq eqty(arr(o_1))$.
- Order o_2 is fully satisfied.

Thus,

$$\alpha = \frac{1}{2} = 0.5 = 50\%.$$

For the **beta service level**, we aggregate the bought and arrived quantities for each item:

- **Item A:**
  - Total bought: $2 + 2 = 4$ units.
  - Total arrived: $1 + 2 = 3$ units.
  - Fulfillment ratio: $\beta_A = \frac{3}{4} = 0.75$.

- **Item B:**
  - Total bought: $3 + 3 = 6$ units.
  - Total arrived: $3 + 3 = 6$ units.
  - Fulfillment ratio: $\beta_B = \frac{6}{6} = 1.0$.

The overall beta service level is then:

$$\beta = \frac{\beta_A + \beta_B}{2} = \frac{0.75 + 1.0}{2} = 0.875 = 87.5\%.$$

This example illustrates how both the alpha and beta service levels can be derived from the QEL data.

6 DISQVER

This chapter provides a description of the disqver application. This includes implementation details and information on the libraries used (Section 6.1) and a typical user journey (Section 6.2).

6.1 Architecture

The disqver application is a web-based system designed for processing and analyzing QEL files. It consists of two main components: 1. A Python-based backend responsible for importing QEL files, executing computations, and deriving key inventory metrics as discussed in Chapter 5. 2. A TypeScript-based frontend, implemented with React[1], providing an interactive user interface for data exploration and analysis.

Backend

The backend is built using FastAPI[2], a modern web framework that enables efficient API development with asynchronous support. FastAPI leverages Pydantic [20] for data validation, ensuring type safety in API parameters and responses. Custom Pydantic validators and assertion checks are integrated to enhance data integrity.
The backend is responsible for:

- Managing file operations, including reading, writing, and caching QEL data.
- Performing demand analysis, lead time analysis, and service level analysis.
- Providing structured data via API endpoints for frontend visualization.
- Storing results in either an SQLite database or JSON files, depending on persistence requirements.

Frontend

The frontend is a single-page web application (SPA) built with React and TypeScript. It communicates with the backend via API requests and enables users to upload QEL files, view structured data, and interact with various analytical components.

The key frontend components include:

- **Upload Component**: Handles user file uploads.

[1] `https://react.dev/`
[2] `https://fastapi.tiangolo.com/`

- **QEL Overview**: Provides a structured summary of the loaded QEL data.
- **Interactive Graph**: Visualizes dependencies using D3.js.
- **Demand Analysis**: Computes and displays demand over time.
- **Lead Time Analysis**: Presents lead times of orders.
- **Service Level Analysis**: Evaluates fulfillment performance.

System Overview

The overall system architecture is illustrated in Figure 6.1. The frontend interacts with the backend through API calls, triggering computations and retrieving data for visualization. The backend processes requests, executes analyses, and manages data storage. The SQLite database and JSON storage serve as persistence layers for structured data.

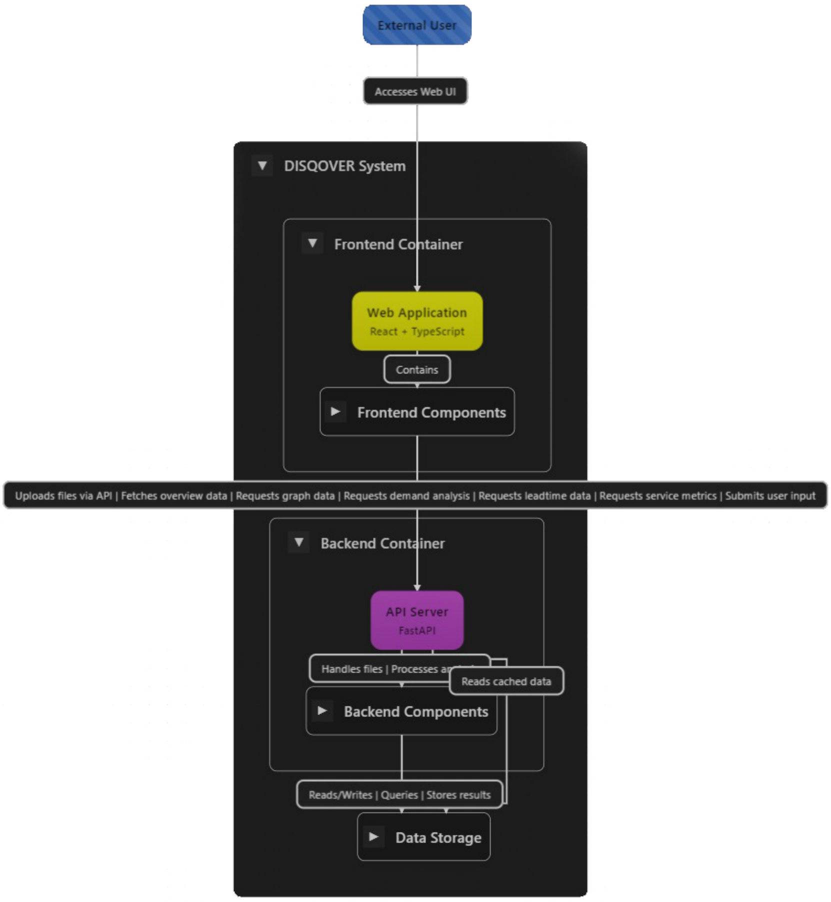


Figure 6.1: Architecture of the disqver application

6.2 User Journey

When opening the Disqver application, the user is first presented with a file upload interface for event logs in the QEL SQLite format. The system requires a valid QEL file to proceed with the analysis.

Once an OCEL file is uploaded, the main dashboard (Figure 6.2) is displayed. The dashboard consists of multiple sections:

- **Overview**: Provides basic dataset information, including the number of events and objects, as well as the filename.
- **Input Information**: Requires the user to specify which object types should be considered as orders and define the type of each collection point.

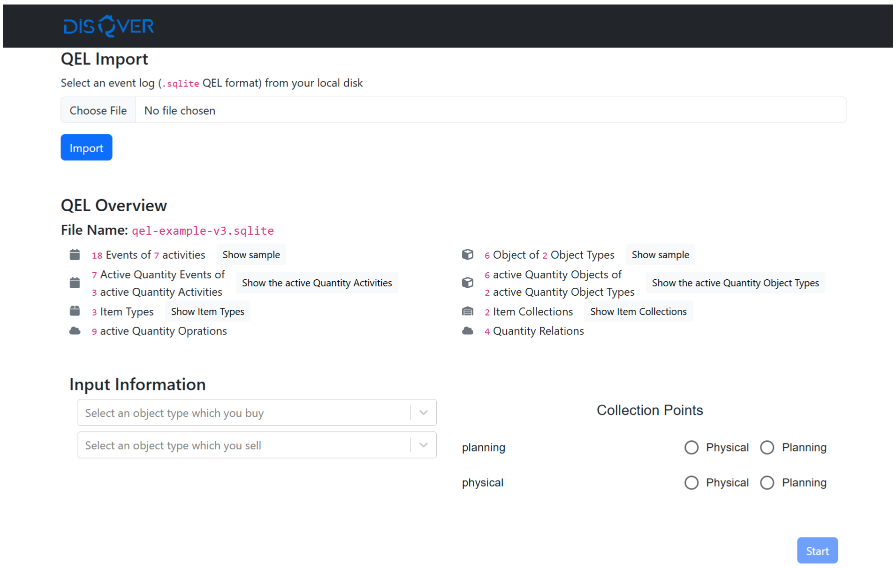


Figure 6.2: Disqver Overview

After providing the necessary input, the user can start the analysis by clicking the *Start* button. The system then processes the data and presents the workflow as a **Quantity Net**, which visualizes material flows within the dataset.
Following the workflow visualization, the user is directed to the main analysis section (Figure 6.3), which consists of three key sections:

- **Demand Analysis**.
- **Lead Time Analysis**.
- **Service Level Analysis**.

Each section allows users to interact with the data, explore trends, and gain insights into the inventory and order management processes.

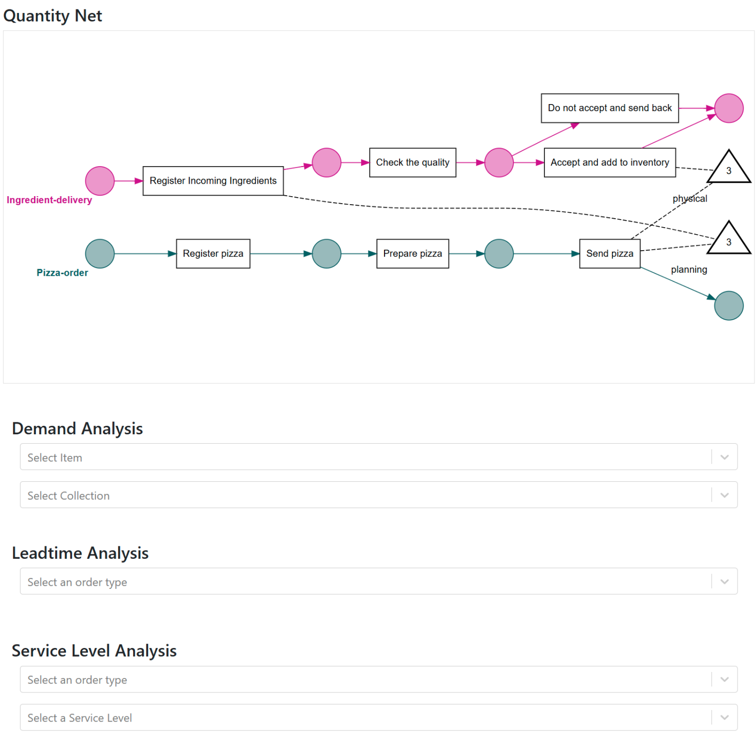


Figure 6.3: Disqver Analysis

7 Evaluation

Nour: Frage nina, ob die diagramme beschreiben werden sollen. also was man darin sieht und so weiter. Oder ein kleine caption reicht. Die diagramme 7.3, 7.4,...

This chapter presents the evaluation of the methods introduced in Chapter 5 and the Disqver application described in Chapter 6. The evaluation is structured around RQ4 and focuses on assessing the effectiveness of the implemented visualizations for the calculated metrics.

In Section 7.1, we introduce the QEL used for evaluation. Section 7.2 presents the visualization results and discusses the insights they provide.

7.1 Input Data

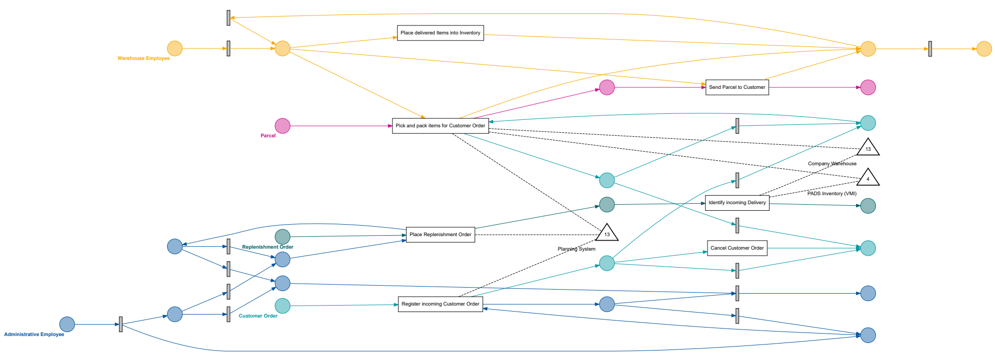


Figure 7.1: Quantity Net from the QEL used for evaluation

The input QEL consists of 8 activities and 7 object types, executed across 3,622 events and 2,725 objects. Additionally, the QEL contains 17 item types and 3 collection points. For this evaluation, we consider the two object types *Replenishment Order* and *Customer Order* as order types.

From the quantity net shown in Figure 7.1, we observe that *Replenishment Orders* are placed during the *Place Replenishment Order* activity and arrive at the *Identify Incoming Delivery* activity.

For *Customer Orders*, placement occurs in the *Register Incoming Customer Order* activity, while delivery is tracked via the *Parcel* object type. Ideally, the arrival activity should be *Send Parcel to Customer*, but due to the absence of a direct mapping between *Customer Orders* and *Parcel* objects in the QEL, this approach is not feasible. Instead, we consider *Pick and Pack Items for Customer Order* as the delivery activity for *Customer Orders*.

Regarding collection points, the *Planning System* is responsible for placing both *Replenishment Orders* and *Customer Orders*, making it the planning collection point. The *Company Warehouse* and *PADS Inventory (VMI)* serve as the physical collection points for these orders.

The corresponding planning collection point for the *Company Warehouse* is the *Planning System*. However, no dedicated planning collection point exists for the *PADS Inventory (VMI)*. Consequently, for item types stored in the *PADS Inventory (VMI)*, service level and lead time calculations cannot be performed.

In the *Company Warehouse* are the following item types:{*Speedometer, Pedal, Brake Cable (2), Handles (2), Tube, Box, Brake Shoes (4), Saddle, Back Light, Tire, Bell, Front Light, Helmet*}. And in the *PADS Inventory (VMI)* are the following item types: {*'PADS Brake Shoes (2)', 'PADS Brake Cable (2)', 'PADS Tire', 'PADS Tube'*}

So the input in the tool will as presented in figure 7.2.

7.2 Results

In this section, we present the visualizations for the calculated metrics, discuss the insights they provide and Justify why this visualization is appropriate. The visualizations are generated using the Disqver application described in Chapter 6.

7.2.1 Demand Analysis

For the evaluation, we focus on two selected item types: *Pedal* and *Front Light*. Two distinct visualization techniques are employed to capture different facets of demand and inventory dynamics:

Monthly Demand: A bar chart (Figure 7.3) is used to display the monthly demand for each item type. Each bar represents the number of units sold during a particular month, which helps in identifying:

- Trends over time (steady, increasing, or decreasing demand),
- Seasonal patterns, and
- Any sudden changes in sales.

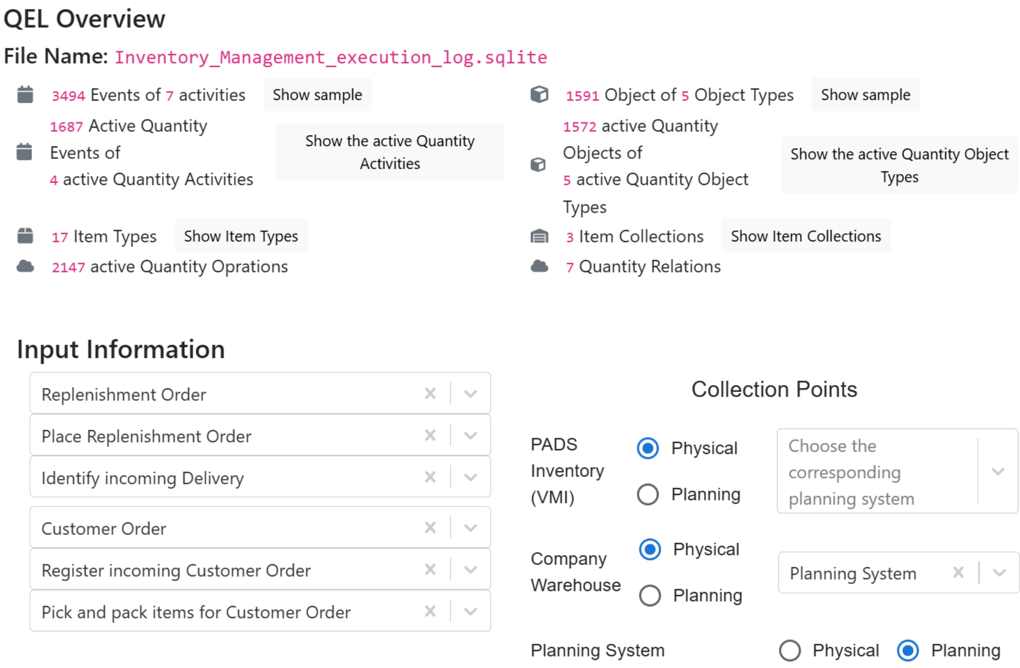


Figure 7.2: Input for the Disqver application

Item Level Development: A line chart (Figure 7.4) illustrates the evolution of stock levels by tracking incoming and outgoing events over time. This visualization makes it possible to:

- Monitor inventory fluctuations,
- Detect stockouts or overstock conditions,
- Evaluate the effectiveness of replenishment policies, and
- Assess whether safety stock levels are appropriate.

Insights Derived: The combination of these visualizations provides valuable insights into inventory management:

1. **Trend Analysis:** The monthly demand chart reveals overall demand trends, allowing identification of items with steady, rising, or falling demand. This is essential for recognizing seasonal effects or shifts in customer behavior.
2. **Forecasting Potential:** Historical demand data can be used to build more accurate forecasting models. A clear understanding of past trends supports better predictions of future sales, thereby optimizing inventory levels.

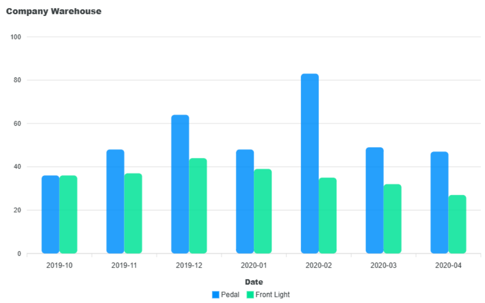


Figure 7.3: Monthly Demand

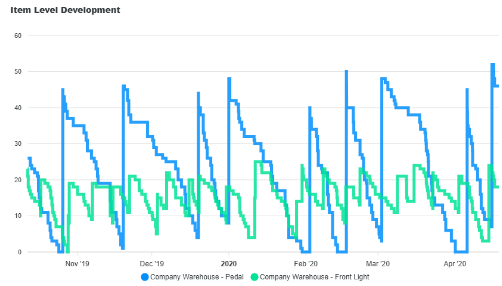


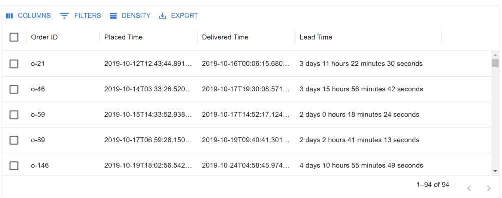
Figure 7.4: Item Level Development

3. **Product Popularity:** Comparing demand across item types highlights which products are more popular, aiding decisions regarding product promotions or discontinuations.

4. **Stock Management:** The item level development chart provides a real-time view of stock variations, which is critical for detecting potential stockouts or overstocking. It also offers insights into order quantities (lot size) and the adequacy of safety stock levels.

Together, these visualizations support data-driven decision-making by offering a comprehensive view of both demand trends and inventory dynamics.

7.2.2 Lead Time Analysis



COLUMNS FILTERS DENSITY EXPORT

Order ID	Placed Time	Delivered Time	Lead Time
o-21	2019-10-12T12:43:44.891...	2019-10-16T00:06:15.680...	3 days 11 hours 22 minutes 30 seconds
o-46	2019-10-14T03:33:26.520...	2019-10-17T19:30:08.571...	3 days 15 hours 56 minutes 42 seconds
o-59	2019-10-15T14:33:52.938...	2019-10-17T14:52:17.124...	2 days 0 hours 18 minutes 24 seconds
o-89	2019-10-17T06:59:28.150...	2019-10-19T09:40:41.301...	2 days 2 hours 41 minutes 13 seconds
o-146	2019-10-19T18:02:56.542...	2019-10-24T04:58:45.974...	4 days 10 hours 55 minutes 49 seconds

1–94 of 94

Figure 7.5: Lead Time Table

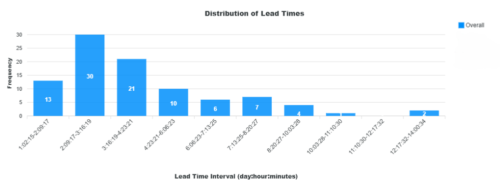


Figure 7.6: Lead Time Distribution

In this evaluation, we focus on *Replenishment Orders* as the representative order type for assessing lead time. Two visualization techniques are used to provide complementary perspectives on the lead time data:

1. **Tabular Representation:** The table in Figure 7.5 presents the calculated lead time for each order individually. This format allows for a detailed, order-level examination and facilitates the identification of specific instances with unusually high or low lead times.

2. **Histogram:** The histogram shown in Figure 7.6 displays the overall distribution of lead times. This visualization is useful for:

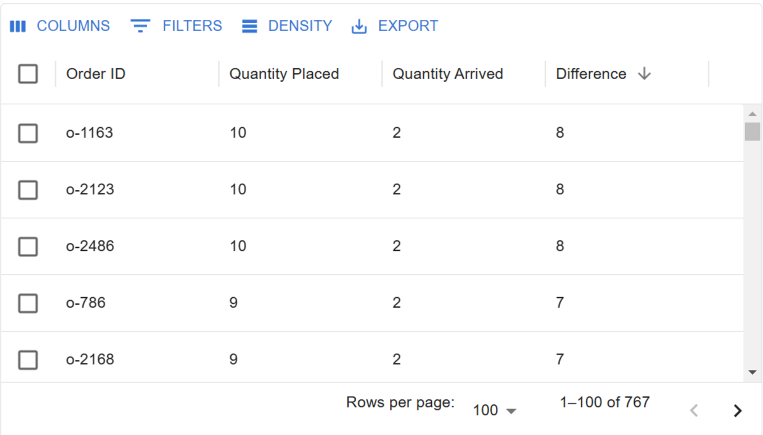
- Identifying the average lead time across orders,
- Analyzing the variability in lead times,
- Detecting outliers or delays in the order process, and
- Determining whether the majority of orders are completed within the expected timeframe.

Together, these visualizations provide a comprehensive view of the lead time performance, offering insights into both individual order performance and overall process efficiency.

7.2.3 Service Level Analysis

For the evaluation of service levels, we focus on the order type *Customer Order*. The analysis considers both the alpha and beta service levels to provide insights into the effectiveness of inventory management in meeting customer demand.

Alpha Service Level



Order ID	Quantity Placed	Quantity Arrived	Difference
o-1163	10	2	8
o-2123	10	2	8
o-2486	10	2	8
o-786	9	2	7
o-2168	9	2	7

Figure 7.7: Alpha Service Level Table

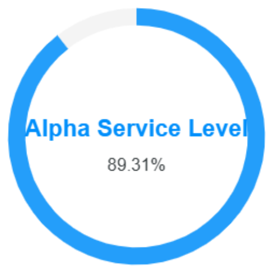


Figure 7.8: Overall Alpha Service Level

The alpha service level evaluates the frequency and extent to which customer orders can be fully fulfilled from available inventory. Two visualization techniques are used:

1. **Tabular Representation (Figure 7.7):** This table details how often customer orders could not be fully met and quantifies the shortfall for each affected order. This information is crucial for identifying recurring stock shortages and assessing their impact on order fulfillment.
2. **Radial Chart (Figure 7.8):** The radial chart presents an aggregated view of the overall alpha service level. A low service level indicates frequent stockouts, which

can lead to customer dissatisfaction and potential loss of sales. If the observed service level is below an acceptable threshold, corrective actions—such as increasing safety stock—may be necessary.

Beta Service Level

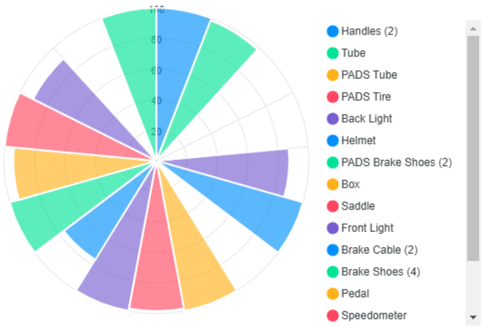


Figure 7.9: Fulfillment Ratio per Item Type

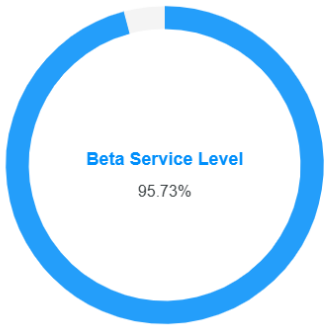


Figure 7.10: Overall Beta Service Level

The beta service level assesses the proportion of ordered quantities that were successfully delivered. This is visualized using two different approaches:

1. **Polar Chart (Figure 7.9):** This chart displays the fulfillment ratio for each item type, helping to identify products with low fulfillment rates that may require further investigation. Such insights can guide improvements in procurement and stock allocation strategies.

2. **Radial Chart (Figure 7.10):** The radial chart provides an overall measure of the beta service level across all customer orders. This metric is particularly useful for evaluating the overall effectiveness of inventory management in meeting customer demand.

If the business has a specific service level target, these visualizations can help assess whether current inventory policies align with expectations. If the observed service levels fall short, adjustments—such as optimizing reorder points or improving supplier reliability—may be required.

8 Discussion

9 Conclusion

This thesis has explored the challenges inherent in modern inventory management within logistics and has demonstrated how data-driven approaches can enhance operational decision-making. By making use of QELs, this work has shown that it is possible to derive key inventory metrics that provide deeper insights into process behaviors and inefficiencies.

The primary problem addressed in this thesis was the inadequacy of conventional process mining techniques to fully support the analysis of inventory management systems. The gap identified in the existing literature, where Quantity Event Logs remain underutilized, served as the motivation for the development of a new method capable of extracting meaningful metrics from such data.

To tackle this problem, a systematic approach was proposed and detailed in Chapter 5. After the meta-review that identified the most relevant performance indicators namely (lead time, demand, and service level). Essential data requirements and event log structures were established, ensuring that the derived metrics capture the complexity of inventory processes.

The implementation of the method is realized in the DISQVER web application, as described in Chapter 6. This tool integrates the derived metrics into a platform that supports detailed visualization and analysis. The application's architecture, based on a FastAPI backend and a React-based frontend, facilitates efficient data processing.

The evaluation presented in Chapter 7 shows the practical benefits of the proposed approach. An analysis performed on a QEL dataset has demonstrated that the method not only enhances the detection of process inefficiencies but also supports more informed, data-driven decision-making in inventory management.

overall this thesis provides a structured framework for the derivation of key inventory metrics from Quantity Event Logs, thereby filling an important gap in process mining research and implementation of the DISQVER application illustrates how these insights can be transformed into actionable tools for inventory control.

9.1 Future Work

There are several promising avenues for future work that could enhance the functionality and applicability of the DISQVER tool. One valuable improvement would be to enable users to upload an OCEL along with a quantity operation table, so that the tool can automatically generate a complete QEL. Since many operations already maintain an OCEL, requiring only the additional quantity operation table would streamline the data preparation process and broaden the tool's usability.

Furthermore, as shown in Table 4.2, a wide range of metrics relevant to inventory management have been identified. Due to the scope of this thesis, only a subset of these metrics has been implemented. Future work should focus on integrating the remaining metrics, which would allow for a more comprehensive evaluation and deeper insights into inventory performance.

In addition to expanding the metric set, further improvements can be made by addressing the limitations discussed in Chapter 8. Enhancing the tool in this way would not only improve its overall functionality and reliability but also adapt it to more complex real-world scenarios.

Another potential extension is to incorporate a quantity operation table for objects, as two of the metrics are currently calculated at the object level. Providing objects with their own quantity operation table would enable more detailed tracking and analysis, thereby increasing the precision of the metrics.

Finally, future work could also explore the integration of additional object attributes into the metric calculations. For example, if a replenishment order includes supplier information, the tool could be extended to calculate the lead time for each supplier individually. This enhancement would provide more granular insights and support targeted decision-making in inventory management.

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