Klaus Huovila

AI-Driven Personalization in B2B E-Commerce Product Recommendations: A Case Study of Etra Oy's B2B Webshop

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Author: Klaus Huovila
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ABSTRACT:

Driven by the growth of digital commerce and the increasing complexity of industrial product catalogues, business-to-business buyers are facing information overload when trying to identify relevant products among tens of thousands of items. How recommender systems are designed is developing, yet empirical research on recommender systems in industrial B2B e-commerce remains limited, particularly from a holistic organisational perspective. This thesis aims to examine the limitations of the current recommender system used in the B2B webshop of Etra Oy, and to answer the research question "How can personalized AI-based product recommendations enhance cross-selling performance in Etra Oy's B2B e-commerce store?".

This study's theoretical background and literature review cover artificial intelligence, different recommender system types, cross-selling in B2B e-commerce, and the DeLone and McLean Information Systems Success Model. This master's thesis is a qualitative single-case study with a pragmatic philosophy and an abductive approach, in which the empirical data were collected through six semi-structured interviews with employees from the case company. In addition, descriptive quantitative data on product sales and webshop user behaviour were used to support and contextualize the qualitative findings.

The findings suggest that the effectiveness of the recommender system is shaped mainly by organizational and data-related factors, rather than by the sophistication of the algorithm itself. The manual, rule-based logic that the company's recommender system is using currently appears to limit scalability, while inconsistent product data and limited resources constrain recommendation coverage. Recommendations, when available, are perceived as accurate and trusted, but approximately sixty percent of products currently lack them. The findings of this thesis highlight that improving recommender system performance in B2B e-commerce, in this case, the company, requires prioritising data standardisation and organisational capacity before implementing advanced AI-driven recommender systems. Rather than transitioning directly toward AI-driven models, a staged approach, which first addresses data inconsistencies and decreases reliance on manual product relationship management seems necessary in order to introduce a scalable and reliable recommendation logic, while taking the B2B needs into consideration.

KEYWORDS: electronic commerce, recommender systems, artificial intelligence, business-to-business commerce, personalisation

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1 Introduction

The growth of e-commerce has led to a large number of products available, making it challenging for buyers to identify relevant items. In B2B settings, where purchase cycles can be long and decision-making often involves multiple stakeholders, this challenge is significant. To address this issue, personalized recommendation systems powered by artificial intelligence are increasingly being used since these can analyze customer behavior, preferences, and transaction histories to suggest related products, and therefore streamline the buying process and boost cross-selling opportunities (Kashef & Pun, 2022). These systems have the potential to directly impact key business metrics, such as average order value and sales revenue (Kashef & Pun, 2022). As B2B e-commerce continues to grow, there is a need for research on solutions that can manage the complexity and scale of modern digital e-commerce stores.

1.1 Background and industry context

AI-driven product recommender systems that can give personalized recommendations are increasingly important, where product catalogues are large, like in the industrial wholesale and supply sector (Olusanya & Isinkaye, 2025, pp. 2–3). Researching this industry addresses many opportunities and critical challenges that are essential for this industry. Below are reasons why researching AI-driven product recommender systems in the industrial wholesale and supply sector's B2B e-commerce stores is important.

One of the key opportunities associated with AI-based recommender systems is the ability to improve sales performance and cross-selling. By processing a large amount of data to find relevant opportunities for cross-selling, these systems can showcase complementary products that would otherwise be unseen by the customer (Olusanya & Isinkaye, 2025, p. 2). Many industrial wholesalers have large catalogues, and finding relevant products can be challenging. Using AI-based recommendation systems to solve that can

lead to higher revenue, which drives business results in the industrial wholesale and supply sector.

In addition to financial performance, recommender systems affect customer experience and retention. Buyers often face information overload, and the problem of information overload can be solved with a recommender system. (Olusanya & Isinkaye, 2025, p. 1). This allows personalized product recommendations to make the purchasing process more streamlined for customers by making it easier for customers to find relevant products fast.

On top of that, as described by Alamdari et al. (2020), digital transformation accelerates in B2B commerce. This said, wholesalers and suppliers that leverage advanced AI tools may gain a competitive advantage. AI-based personalization allows businesses to respond to changes (Alamdari et al., 2020), and this can allow them to tailor offerings to specific customer segments and differentiate the business in the crowded marketplace. Delivering data-driven and relevant personalized recommendations also increases customer loyalty in competitive domains (Olusanya & Isinkaye, 2025, p. 3). For these reasons, researching B2B recommender systems matters in the industrial wholesale and supply sector industry. This thesis will conduct research specifically on Etra Oy, which is a Finnish technical sales specialist that provides a comprehensive range of industrial products and services, serving as a trustworthy partner for customers in various industrial sectors (Etra Oy, n.d.). The case company operates through multiple sales channels, including physical stores and a B2B e-commerce store (Etra Oy, n.d.).

1.2 Research gap

Recommender systems are well researched in the B2C context, but the academic literature on recommender systems in B2B electronic commerce is limited (Cho et al., 2023). Current studies mainly focus on technical performance, with little focus on cross-selling

or broader business impact. The lack of a comprehensive evaluation framework usage is another gap in the literature. Using the Information Systems Success Model, for example, allows the evaluation of user satisfaction, system quality, or organizational benefits in B2B e-commerce settings. There is limited understanding based on the current literature on how AI-driven recommender systems perform in a B2B environment from a technical and business value perspective as a whole.

This research gap is important because industrial distributors often work with very large and specialized product data, resulting in customers struggling to find relevant complementary items from e-commerce stores. Many companies rely on simple, not optimized approaches, such as cross-basket logic, which do not work optimally with large data sets from B2B stores, which can limit cross-selling. This showcases a practical need for research on how to improve recommender systems and drive business value through B2B e-commerce product recommendations based on a real-world case study.

This thesis addresses existing research gaps by empirically evaluating the case company's current recommender system using the ISSM framework. The analysis identifies operational limitations of the rule-based B2B recommender system, assesses organizational data sources, and examines how AI-driven personalization approaches identified from prior research may inform the development of more effective cross-selling capabilities.

1.3 Research Objectives

The objective of this thesis is to examine the limitations of the current product recommender system used in Etra Oy’s B2B e-commerce store and to explore how AI-driven product recommender system approaches identified in existing research could improve cross-selling performance and inform future system development. The main research

question of the thesis is: *How can personalized AI-based product recommendations enhance cross-selling performance in Etra Oy's B2B e-commerce store?*

To support the research of this topic and to answer the main research question in a coherent way, this thesis consists of four sub-research questions to break down the issue:

1. *What are the limitations of the current recommender system used in Etra Oy's B2B e-commerce store?*
2. *Which data sources at Etra Oy can be utilized to improve product recommendations at the company's E-commerce store?*
3. *What evidence does existing research provide about the effectiveness of AI-driven personalization on cross-selling performance in e-commerce, and how does this evidence translate into the industrial B2B context?*
4. *What managerial implications arise for Etra Oy when considering the adoption of the new recommender system across international markets?*

1.4 Structure of the Study

The rest of the thesis is structured as follows: Chapter 2 presents the theoretical background of the study by reviewing existing literature related to artificial intelligence, recommender systems, and personalization in e-commerce. The chapter introduces and defines the key concepts relevant to the study, including artificial intelligence, product recommender systems, and the Information Systems Success Model (ISSM). In addition, it discusses different types of recommender systems, their benefits and limitations, and the key differences between B2C and B2B e-commerce contexts. This chapter primarily addresses the third sub-research question: "What evidence does existing research provide about the effectiveness of AI-driven personalization on cross-selling performance in e-commerce, and how does this evidence translate into the industrial B2B context?".

Chapter 3 describes the methodology used in this thesis. It explains the research philosophy, research approach, and research strategy, as well as the case study design. Furthermore, the chapter outlines the data collection methods, including semi-structured interviews and supportive quantitative data, and describes the data analysis methods applied in the study.

Chapter 4 presents the empirical findings of the thesis. The chapter begins with a brief introduction of the case company and its B2B e-commerce context. The empirical analysis is divided into two complementary parts. First, a descriptive quantitative analysis is presented to assess data availability, structure, and usability in relation to product recommendations. This analysis supports the second sub-research question: “Which data sources at Etra Oy can be utilized to improve product recommendations at the company’s B2B e-commerce store?”. Second, the main empirical analysis is conducted through a thematic analysis of semi-structured interviews with multiple organizational stakeholders. This qualitative analysis addresses the first sub-research question: “What are the limitations of the current recommender system used in Etra Oy’s B2B e-commerce store?” and provides empirical insights relevant to the fourth sub-research question concerning managerial implications and organizational considerations related to adopting more advanced recommender systems across international markets.

Chapter 5 discusses the findings of the study in relation to the theoretical framework and prior literature. The chapter synthesizes the empirical results and presents managerial implications for the case company, Etra Oy. In addition, the chapter discusses the limitations of the study and provides suggestions for future research.

2 Theoretical Background and Literature Review

This chapter introduces and defines the main theoretical concepts relevant to this thesis. The purpose is to develop a comprehensive understanding of the underlying themes that support the analysis in later sections. Instead of presenting all available theories, the chapter focuses on the concepts most relevant to the research. These concepts are artificial intelligence, recommender systems, and the Information Systems Success Model (ISSM). Additionally, the chapter synthesizes and analyzes existing research on this topic and helps address the third sub-research question by identifying what existing research suggests about the effectiveness of personalized product recommendations.

2.1 Artificial Intelligence Definition

Since artificial intelligence is the underlying technological foundation of recommender systems, it is important to clarify what AI is and how it is defined. Artificial intelligence, which started from computer science, is a fast-growing topic in many fields (Li & Jiang, 2017). There are multiple definitions of artificial intelligence, and there is no one commonly accepted definition of AI (Li & Jiang, 2017). To get a better understanding of how AI can be defined, here is one definition used for AI in current research: “A system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation” (Kaplan & Haenlein, 2019, p. 1).

Artificial intelligence is a broad scientific discipline with several subfields, including machine learning and deep learning, natural language processing, computer vision robotics and intelligent systems, among others (Belfiore et al., 2022).

2.2 Recommender Systems

Recommender systems are widely regarded as an application of artificial intelligence, particularly within the machine learning subfield, as modern recommender systems are commonly based on machine learning techniques (Goodfellow et al., 2016). In electronic commerce environments, such systems are commonly used to support user decision-making by reducing information overload and highlighting relevant products.

2.2.1 Relationship of recommender systems and AI

There are hierarchical relationships in AI fields: deep learning is a subset of machine learning, which is one of the major subdomains of AI (Goodfellow et al., 2016). The deeper the level within this hierarchy, the less dependent the system is on human-defined rules. In traditional AI approaches, decision rules are explicitly programmed by domain experts, whereas in machine-learning-based approaches, the system learns patterns and relationships directly from data. (Goodfellow et al., 2016). One of the primary uses of machine learning is to generate recommendations by estimating the relationship between a user and a product, the likelihood of a particular action, or the potential value that an item may provide to that user. The earliest recommender systems were built on the idea of identifying similarities between users (Goodfellow et al., 2016).

Borges et al. (2021) illustrate this distinction using e-commerce product recommendations: a rule-based AI model recommends products according to a predefined rule, such as "if the customer purchased product A, recommend product B," whereas a machine-learning model infers these associations autonomously from purchase histories and behavioral data.

To visualize this relationship between AI disciplines, Figure 1. shows how recommender systems, machine learning, and artificial intelligence are related to each other.

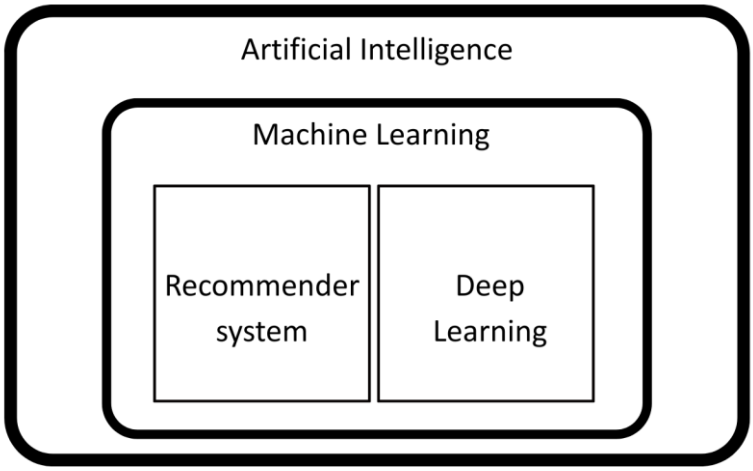

Figure 1. Relationship between AI disciplines. (author's elaboration based on Goodfellow et al., 2016).

2.2.2 Recommender system definition

Recommender systems effectively leverage a large amount of data to recognize user habits and personalization trends, and their effectiveness has grown alongside the fast-growing volume of data (Roy & Dutta, 2022, p. 1). As described by Burke (2002), recommender systems are valuable in situations where the user has many available options and exceeds the capacity to process them. Recommendation systems play a crucial role in the domain of e-commerce (Burke, 2002). Companies like eBay and Amazon have been using recommender systems in their electronic commerce sites since the 1990s (Schafer et al., 1999). For electronic commerce stores, recommender systems are business tools that are reshaping online business (Schafer et al., 1999). This enables customers to discover relevant products to purchase.

Recommender systems are also referred to as personalized systems. In practical applications, such a system functions by processing data to deliver tailored results within larger and more complex real-world environments that often come with architectural and data constraints (Ricci et al., 2011). Recommender systems collect data of users' preferences and recommend tailored services or products as a result (Li & Karahanna, 2015). In e-commerce stores, these systems help customers discover relevant products to buy (Li &

Karahanna, 2015). Recommender systems can make recommendations based on different criteria such as past buying behavior and demographics data (Schafer et al., 1999).

Despite the notable accuracy of recommender systems, they face challenges such as scalability, cold-start issues, and sparsity, and the number of techniques available complicates the selection process for application-specific systems. Each of the systems comes with distinct features, advantages, and disadvantages (Roy & Dutta, 2022, p. 1). Recommendation systems are typically categorized into content-based filtering, collaborative filtering, and hybrid filtering methods (Roy & Dutta, 2022).

2.3 Types of recommender systems

The following subsections examine the three main types of recommender systems: collaborative filtering, content-based filtering, and hybrid models. Each is discussed in terms of its underlying logic, strengths, and limitations.

2.3.1 Collaborative Filtering

Collaborative filtering is the most used approach in recommender system design. It plays a crucial role in the recommendation process, and it is often used together with other filtering techniques, such as content-based or knowledge-based filtering (Lü et al., 2012). E-commerce platform Amazon uses this method to deliver personalized product recommendations by utilizing user behavior and ratings (Jiang et al., 2019). Collaborative filtering methods rely on the collection and analysis of extensive data regarding user behavior, activities, or preferences to predict a user's tastes based on their similarities with other users.

This method first finds a group of users X, whose likes, dislikes, and preferences are similar to user A. In this case, X is called the neighborhood of A. Then the items that are liked

or preferred by the majority of the users X are recommended to user A (Roy & Dutta, 2022). This approach does not need any information about item features for creating a recommendation, and it can help to expand the user's current interests by discovering new items (Roy & Dutta, 2022).

Collaborative filtering is divided into two main types: memory-based approach and model-based approach (Roy & Dutta, 2022). Memory-based collaborative methods suggest items by analyzing the preferences of similar users within a given neighborhood and can be further subdivided into user-based and item-based collaborative filtering (Roy & Dutta, 2022). The user approach finds other users from the same user neighborhood, and the user rating of a new item is calculated based on how other users in the neighborhood have rated it. User-based collaborative filtering is visualized in Figure 2. below. The item-based approach, on the other hand, creates an item neighborhood of similar items to the new one. The new item will be recommended based on the user's previous ratings of similar products in the neighborhood (Roy & Dutta, 2022). Item-based collaborative filtering is visualized in Figure 3.

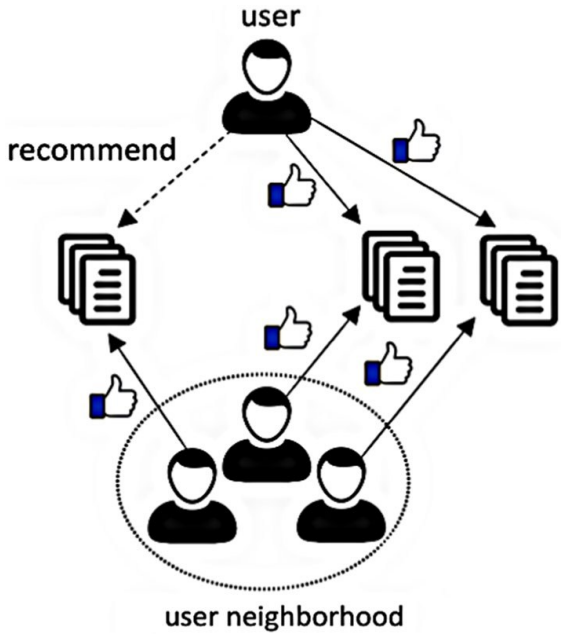

Figure 2. User-based collaborative filtering (Roy & Dutta, 2022, p. 5).

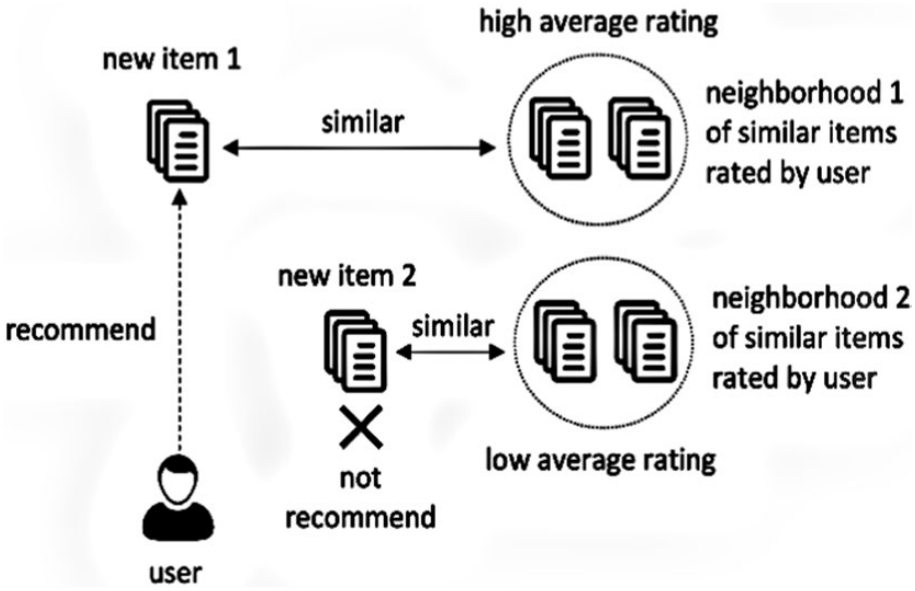

Figure 3. Item-based collaborative filtering (Roy & Dutta, 2022, p. 5).

A model-based recommendation system is created by extracting some information from a dataset and using that as a "model" to make product recommendations without having to use the whole dataset in every recommendation. It is beneficial for speed and scalability, and the model-based approach can improve the prediction accuracy of algorithms (Roy & Dutta, 2022).

There are distinct advantages but also disadvantages in using a collaborative filtering approach in an e-commerce product recommender system. The main problems of the collaborative filtering system are data sparsity, cold start, and poor scalability (Jiang et al., 2019, p. 3024). The cold start problem occurs when there is no data of the new user or few interactions with items, which reduces the recommendation efficiency for the newcomers (Nguyen et al., 2023, p. 1). Jiang describes that in extensive catalogs, the sparsity of user-item interaction matrices frequently results in unreliable recommendations and diminished accuracy (Jiang et al., 2019). The main advantages of this system are personalization and relevance. Collaborative filtering can analyze user interactions and preferences and often results in increased user engagement and sales (Jiang et al.,

2019). The collaborative filtering system can also find novel products using data of similar users (Roy & Dutta, 2022), which can be a strength in a B2B e-commerce store. Since the system creates recommendations based on similar users or items, the system does not need detailed product information (Roy & Dutta, 2022).

2.3.2 Content-Based approach

A content-based approach is another way a recommender system logic can be created for an e-commerce store. Historically, the two main recommender system approaches have been collaborative filtering and the content-based approach (Lops et al., 2019). This is less typical to be used in product recommender systems compared to the collaborative filtering approach. However, it has its own strengths and weaknesses, different from collaborative filtering. This type of recommender system makes item recommendations based on both the user's past interactions and item data. This data includes descriptions and characteristics of the user and item (Lops et al., 2019). A content-based recommender system builds a profile of the user based on previously interacted content by the same user and recommends items with similar features to the ones previously dealt with (Pazzani, 1999). The operation of a content-based recommender system includes three essential parts. 1) item representation, 2) user profile generation, and 3) a learning component, which creates product recommendations and the user-product matching (Lops et al., 2019).

The main advantage of using a content-based approach is that it is great at solving the cold start problem for items, meaning that when a new item is added to a B2B e-commerce store, it can still be recommended despite the lack of interactions with this product. Compared to collaborative filtering, which needs historical interactions with products, like product ratings, to create item similarity and recommend it to users, a content-based approach can right away recommend a new item if there is content, like features or product description, which the system can analyze attached to the item (Lops et al.,

2019). This allows new niche products with a broad description to be seen as well by the buyers.

One aspect to take into consideration in the B2B e-commerce product recommender system context is that using a content-based filtering approach leads to strong user independence and transparency. Since recommendations are entirely made based on the individual's past interactions and the item information, the product recommendations are independent of the preferences of any other users' preferences and things such as other product ratings do not affect the recommendations (Pazzani, 1999). Transparency in a content-based approach means that it can be explained simply that, e.g., products X, Y, Z are recommended, because the customer has purchased item A, which has many similar features to the items X, Y, Z (Ricci et al., 2011). This can be beneficial in B2B transactions where justifications of the buying decision must consider the organizational need (Zhang & Wang, 2015).

However, there are some disadvantages to the content-based filtering approach. The system has a challenge with overspecialization (Lops et al., 2019). Since the system recommends only items similar to those a user has previously interacted with, it offers limited product diversity and may prevent users from discovering new relevant products. This can also lead to showing the same product recommendation repetitively (Lops et al., 2019).

2.3.3 Hybrid Model approach

The core limitations of single recommendation systems, like the cold-start problem and data sparsity in collaborative filtering systems, and the challenge of overspecialization in content-based filtering, as previously mentioned, have led to the use of more sophisticated systems. The solution to these challenges is the use of a hybrid recommendation system, which can combine many filtering techniques to improve product recommendation coverage and accuracy (Bodduluri et al., 2024).

Hybridization is defined as the integration of many algorithms and the use of diverse weighting methods to minimize the limitations of any individual algorithm (Bodduluri et al., 2024, p. 28274). The hybrid approach directly solves the main weaknesses of the most established models highly effectively in e-commerce, and it often combines content-based and collaborative filtering methods to overcome data sparsity and cold-start problems (Rifqi et al., 2025, p. 1983). By integrating two or more algorithms, hybrid recommender systems are designed to create recommendations that are more accurate, personalized, and responsive to customer behavior changes (Bodduluri et al., 2024, p. 28275).

Hybrid systems have clear advantages over single architecture models that are important for optimizing sales performance and user experience in B2B e-commerce stores.

1. Improved accuracy and personalization. Hybrid recommender systems surpass the limitations of single recommender systems and can provide tailored product recommendations with better accuracy by combining several algorithms to understand the customer's preferences and interests (Bodduluri et al., 2024, p. 28275).
2. Improved adaptability and robustness. Differing from singular algorithms, which a lot of times struggle with data inconsistencies and sparsity, the hybrid approach maintains performance stability. It can work robustly and deal well with users' changing behaviors and item preferences (Bodduluri et al., 2024, p. 28275), which ensures continuous reliability in the system.
3. Broader coverage and diversity. Single recommendation systems recommend products utilizing less data, which can lead to only recommending a small number of relevant products to the customer. However, hybrid recommender systems exceed these limits and give more diversified recommendations (Bodduluri et al., 2024, p. 28275).
4. Flexibility. The hybrid model is generally seen as more adaptive and flexible when it comes to utilizing different data types and using them in applications. This

makes it a strong system for complex e-commerce platforms (Rifqi et al., 2025, p. 1989), which B2B e-commerce stores often are.

In e-commerce, the most effective hybrid systems are a structural combination of strategic integration of collaborative filtering and content-based filter methods, which has been considered a great foundation for numerous recommender systems (Bodduluri et al., 2024, p. 28280). Previous findings highlight that approximately 80% of proposed solutions designed to overcome significant challenges in recommender systems utilize the combination of content-based filtering and collaborative filtering as their foundational base (Bodduluri et al., 2024, p. 28282). Hybrid architectures are realized through seven identified types of hybridization: "Weighted Hybridization, Switching Hybridization, Cascade Hybridization, Mixed Hybridization, Feature-Combination, Feature-Augmentation, and Meta-level" (Rifqi et al., 2025, p. 1987). Out of those seven types, Weighted Hybridization is the most used because it is effective in making the recommendations more accurate (Rifqi et al., 2025, p. 1983).

2.3.4 Comparison of the models

Table 1 below summarizes the key strengths and weaknesses of Collaborative Filtering, Content-Based, and Hybrid recommender systems, based on the literature review, and emphasizes the applicability of the models to the B2B industrial e-commerce context.

Table 1. Key strengths and weaknesses of different types of recommender systems.

Approach	**Key Strengths**	**Key Weaknesses**	**System Assumptions**	**Data Requirements**	**Fit for B2B E-Commerce Catalogues**	**Relevance to This Thesis**
Collaborative Filtering (CF)	- Learns from historical co-purchase and user–item interactions	- Does not work well with sparse data, which is typical	Assumes that users	Requires large volume of historical	**Low - moderate**: B2B distributors tend to have	Commonly used approach as a baseline in many B2B

Approach	Key Strengths	Key Weaknesses	System Assumptions	Data Requirements	Fit for B2B E-Commerce Catalogues	Relevance to This Thesis
	(Jiang et al., 2019) - Performs well when extensive user–item interaction data is available (Jiang et al., 2019)	issue in B2B (Jiang et al., 2019) - Weak performance with infrequent transactions (Saraei et al., 2025) -Performs badly in cold-start situations involving new users or new products (Nguyen et al., 2023) - Limited recommendations explainability (Heckel et al., 2017)	with similar purchase patterns will prefer similar items in the future (Roy & Dutta, 2022)	purchase data, performs poorly with sparse datasets (Jiang et al., 2019)	infrequent, long-tail transactions, which can lead to limited data and therefore less accurate recommendations	recommender systems
Content-Based (CB)	- Performs well with rich product metadata (descriptions, attributes) (Lops et al., 2019) - Independent of user interaction volume (Pazzani, 1999) - No cold-start problem with new items (Lops et al., 2019)	- Cross-product relationships are not analyzed (Cho et al., 2023) - Limited ability to discover new/novel items for a customer (Lops et al., 2019) - Consistent, high-quality product data is needed	Assumes that item similarity can be analyzed based on product features	Requires structured and detailed product metadata, but minimal user data (Lops et al., 2019)	**Moderate**: Works if the data is well structured, limited for complex industrial items where there is a lot of specifications (Saraei et al., 2025)	Relevant for evaluating how product features can be used in recommendation logic and how hybrid models can enrich item data

Approach	Key Strengths	Key Weaknesses	System Assumptions	Data Requirements	Fit for B2B E-Commerce Catalogues	Relevance to This Thesis
	- Transparent and explainable recommendations (Ricci et al., 2011)	(Shambour & Lu, 2015)				
Hybrid Approaches	- Combines strengths of CF and CB (Rifqi et al., 2025) - Avoids sparsity and cold-start problems (Rifqi et al., 2025) - Utilized cross-product patterns and item similarity (Boddu-luri et al., 2024) - Flexible and customizable for specific needs (Rifqi et al., 2025)	- Complex in design and maintenance (Rifqi et al., 2025) - Requires more computational resources (Rifqi et al., 2025) - Model transparency varies depending on the design (Heckel et al., 2017)	Assumes that multiple data sources can be integrated effectively	Needs both user–item interaction data and product metadata (Rifqi et al., 2025)	**High:** Handles many issues from CF and CB, like sparsity, large catalogue data. Typically used in industrial B2B settings (Nia et al., 2019)	Most relevant to thesis: Hybrid models have proven to outperform simple CF in industrial distributor studies (Saraei et al., 2025)

2.4 Application and Challenges in B2B E-commerce

B2B buying decisions focus on the organization's needs and are often more complex compared to B2C transactions (Zhang & Wang, 2015, p. 54), and this makes a hybrid approach beneficial for B2B e-commerce stores. Professional buyers in the B2B context can also receive assistance in purchasing by the recommender system (Zhang & Wang, 2015, p. 53). A hybrid recommender system is beneficial in complex cases, like aiding professional purchasers in navigating complex modified rebuy scenarios, enhancing their efficiency and effectiveness (Zhang & Wang, 2015, p. 54).

The B2B environment naturally mitigates data sparsity issues that drive the transition to hybrid systems in B2C e-commerce stores (Zhang & Wang, 2015, p. 60). Even though the lower impact of data sparsity, the implementation of a B2B hybrid recommender system requires extensive customization, with optimal outcomes reliant on developers selecting methods tailored to product attributes, user needs, and industry characteristics. The customization needs mean that there is no single model that is universally the best (Zhang & Wang, 2015, p. 58).

The main challenge of implementing an advanced hybrid recommender system is its complexity, and if this recommender system is implemented, it can require significant investment and resources from the company. For that reason, selecting and implementing hybrid methods for an e-commerce store must consider both the potential benefits and available resources (Rifqi et al., 2025, p. 1989).

2.5 B2B vs. B2C E-commerce product recommender system

Recommender systems have been commonly used in B2C e-commerce stores, where the most important thing is to help consumers navigate a large number of products (Zhang & Wang, 2015, p. 54). Compared to B2C, consumption in the business environment, purchasing processes, and decision structures differ fundamentally; for example, multiple stakeholders may decide on the buying decisions, and the purchases need to consider the organization's needs (Zhang & Wang, 2015, p. 54). In B2C stores, buyers are often individuals, but in B2B e-commerce stores driven by recommender systems, users are often professional buyers or sales teams from a company, meaning the audiences differ between B2C and B2B stores (Heckel et al., 2017, p. 1035).

Another significant difference is the value and risks regarding product recommendations. In B2C, product recommendations often have relatively small financial value (Heckel et

al., 2017, p. 1035). When, on the other hand, in a B2B environment, the product recommendations can result in a purchase of expensive equipment or large quantity orders, which ends up generating thousands or even millions in revenue (Heckel et al., 2017, p. 1035). These requirements and differences between B2C and B2B needs have driven the development of B2B-specific models, which go beyond traditional latent factor approaches that lack transparency for professional buyers (Heckel et al., 2017).

A B2B e-commerce store's technical environment also presents unique challenges. Industrial distributors can have tens of categories containing hundreds of thousands of products. This can, at this scale, increase the risk of customer information overload and increase the data sparsity problems in collaborative filtering models (Nia et al., 2019, p. 337). To address these challenges, B2B recommender systems often rely on combining enterprise back-end data, like user information, historical purchasing history and long-term organization data from ERM or CRM systems (Zhang & Wang, 2015, pp. 53, 56). The need for integration across multiple enterprise systems, transparency, and rigorous data suggests that hybrid or context-aware systems may be better suited for recommender systems in B2B e-commerce stores compared to collaborative or content-based models (Nia et al., 2019). These reasons highlight why recommender system development in B2B needs high consideration and not just direct transfer of B2C techniques (Zhang & Wang, 2015). In the context of this thesis, these characteristics are directly relevant for the understanding of opportunities and limitations affecting the development of an AI-driven product recommender system.

2.6 Cross-Selling & AI-Based Recommendations

Cross-selling is an important mechanism to increase revenue in e-commerce. Kashef and Pun (2022, p. 2) define cross-selling as a process that "identifies products that satisfy additional, complementary needs unfulfilled by the primary item to increase the value of a sale." Well-performing cross-selling systems rely on a recommendation system,

which suggests additional products to customers and increases the average order value and number of products purchased per customer (Kashef & Pun, 2022, p. 1).

2.6.1 Rule-based vs. AI-based approaches

Traditional methods in identifying cross-selling possibilities are usually based on rule-based approaches, in particular Association Rule Mining, which finds correlations between variables in a large amount of data (Kashef & Pun, 2022, p. 3). Later, an approach, Frequent Itemset Mining, was created based on Association Rule Mining, and it has been used in cross-selling in multiple rule-based solutions (Kashef & Pun, 2022, p. 3). However, when the dataset grows, the rule-based models face constraints and limit the scalability of the system (Kashef & Pun, 2022, p. 5).

However, modern cross-selling models driven by AI have demonstrated superior empirical performance in speed and accuracy compared to traditional methods (Kashef & Pun, 2022, p. 1). For example, a hybrid model created by Kalkan and Şahin (2023, p. 6248) can integrate more behavioral and contextual information, leading to more accurate complementary item predictions. This was created as a practical solution to a problem of many electronic commerce stores of how to increase the cross-selling performance by estimating the probability of which product customers will purchase next (Kalkan & Şahin, 2023, p. 6250).

Hybrid AI approaches offer other advantages as well. For example, clustering-based I-CrossSold model, which Kashef and Pun (2022, p. 2) describe as effectively finding the best cross-selling opportunities based on customers' historical purchase and preference data, like product contexts. Collectively, empirical studies show that AI-driven models have better results in speed, accuracy, contextual relevance, and adaptability to customer behavior, making these suitable for cross-selling solutions.

2.6.2 Relevance to B2B Cross-Selling

Even though a lot of the empirical research on AI-driven cross-selling is done in B2C contexts, the insights of these findings translate well into B2B. Modern AI models can utilize contextual information like “selling price, purchasing price, and the cross-association score between products” (Kashef & Pun, 2022, p. 11). This corresponds well with the complex buying decisions in B2B, where things like operational needs and margins drive purchasing decisions. In addition, hybrid AI-driven recommender methods that enhance sparse interaction data and tackle synonym issues are especially relevant in B2B settings that have large product ranges and infrequent transactions (Saraei et al., 2025).

In summary, the evidence shows that AI-based recommender systems, especially hybrid and contextual models, are superior compared to rule-based models in cross-selling in B2B e-commerce stores.

2.7 Summary of Prior Empirical Research on B2B Recommender Systems

There is notably less empirical research conducted on B2B recommender systems compared to targeting B2C companies, regardless of the growth of e-commerce in both sectors (Cho et al., 2023). Recent studies consistently highlight structural challenges in B2B environments, including data sparsity resulting from infrequent and high-value transactions. For example, Saraei et al. (2025) show that data sparsity remains a central challenge in B2B recommender systems because transactions are highly specialized and occur infrequently. Such conditions limit both the performance and explainability of traditional collaborative filtering models, motivating researchers to design more robust and transparent approaches tailored to B2B environments.

Across empirical B2B studies, many methodological patterns emerge. Hybrid and knowledge-intensive approaches that use complex side information have been

presented. For example, a study by Shambour and Lu (2015), where hybrid-trust based models have been empirically tested on B2B case studies, shows results that hybrid-based models significantly outperform collaborative filtering. Similarly, studies related to industrial distributors confirm advanced hybridization techniques' effectiveness by creating larger item matrices by combining Association Rule Mining (ARM) with advanced decomposition methods to address problems of sparsity and product similarity in a B2B electronic commerce store (Saraei et al., 2025, pp. 1–2).

A recent empirical study has also introduced a new application model specifically for B2B requirements, for example, the Knowledge Graph Attention Network model, not necessary to recommend products, but to predict and match potential buyers to sellers (Cho et al., 2023, p. 1). The approach introduced by Cho et al. (2023, p. 2) underlines the complexity of B2B relationships and, importantly, demonstrates explainability for recommendations. These studies have contributed to valuable technical insights on B2B recommender systems; however, they lack assessing in-depth practical business outcomes.

Table 2 below summarizes the most relevant prior empirical studies on B2B recommender systems. It highlights methodologies, contexts, and key findings of those studies as well as creates a basis for identifying key research gaps relevant to this thesis.

Table 2. Summary of prior empirical studies on B2B recommender systems

Study (Author, Year)	**Company/Sector Studied**	**Data Used**	**RS Approach Tried**	**What Was Found**	**Relation to Thesis**
Shambour and Lu (2015)	B2B Business Partner (Australian Suppliers Directory)	BizSeeker dataset (1,602 ratings; 95.2% sparsity) (Shambour & Lu, 2015, p. 1123).	Hybrid User-Item Trust (HUIT) combining implicit user and item trust (Shambour & Lu, 2015)	HUIT significantly outperformed benchmark algorithms in accuracy (MAE) and coverage on B2B data (Shambour & Lu, 2015).	Feasibility: Validates hybrid models for B2B. Alignment: Does not target cross-

Study (Author, Year)	Company/Sector Studied	Data Used	RS Approach Tried	What Was Found	Relation to Thesis
					selling or utilize ISSM.
Saraei et al. (2025)	Industrial Distributor (Quebec, Canada)	Real-world transactional data (10 million records, 15,000+ items) (Saraei et al., 2025, pp. 4-5).	Hybrid CF (Taxonomy + ARM + i-ALS/SVD++) (Saraei et al., 2025)	Proposed hybrid method achieved superior accuracy over four baselines by reducing data sparsity and item synonymy (Saraei et al., 2025)	Direct Alignment: Focuses on an industrial distributor with a large catalogue using hybrid methods to enhance item data.
Cho et al. (2023)	Korean B2B Market (Multiple Sectors)	Market Transaction Dataset (347,388 interactions; 99.66% sparsity) (Cho et al., 2023, p. 7).	Knowledge Graph Attention Network (KGAT) (Cho et al., 2023)	KGAT proved effective for recommending potential buyers to sellers and offered essential explainability through attention scores (Cho et al., 2023, p. 3).	Explainability: Addresses the critical need for justification in B2B. Context: Deals with high sparsity and complex relations.
Wu et al. (2015)	Large data sets, Australian business dataset, MovieLens Dataset (Wu et al., 2015, pp. 38–39).	Business ratings reflecting complex, hierarchical product/service structures (Wu et al., 2015)	Fuzzy Preference Tree-Based approach (Wu et al., 2015)	Fuzzy Tree model achieved lowest MAE and highest F1 on tree-structured data, supporting accurate recommendations for complex	Large Catalogue: Confirms the need for handling complex, hierarchical product data structures common in

Study (Author, Year)	Company/Sector Studied	Data Used	RS Approach Tried	What Was Found	Relation to Thesis
				items (Wu et al., 2015, pp. 39–40).	industrial catalogs.
Nia et al. (2019)	B2B Industrial Retailer (Conceptual Framework)	Simulates large, diverse product data, 100,000 text lines, (Nia et al., 2019, p. 5)	Hybrid Framework (Nia et al., 2019)	Framework is suitable for overcoming information overload and managing the vast number of items characteristic of B2B industrial retail (Nia et al., 2019, p. 1)	Industrial Context: Directly addresses the problem domain (industrial distributor, large catalog, side information

Even though empirical studies researching B2B recommender systems have provided valuable technical insights, significant research gaps remain. These gaps concern in particular the B2B recommender systems in the industrial supply and solutions industry, and evaluation of B2B recommender systems in e-commerce stores based on a comprehensive evaluation framework that analyzes business impact.

The first research gap identified is the direct linkage to cross-selling performance. Multiple studies have targeted feasibility or maximizing recommendation accuracy in B2B stores, but there is a lack of case studies that research cross-selling performance in the large-catalogue industrial sector. The second research gap identified is that current empirical studies compare new recommender systems typically with general collaborative filtering, random, or the most popular baseline models. There is a need for research comparing AI-driven personalization models with industry standards to demonstrate tangible value. The third research gap identified is having a holistic business value evaluation from recommender systems. Currently existing research on B2B research focuses heavily on technical metrics. There is a significant gap in research utilizing information system business evaluation frameworks, like the Information Systems Success Model.

This would allow validation of AI-driven recommender systems beyond technical metrics, including, for example, system quality and net benefits for the organization.

2.8 Information Systems Success Model (ISSM) as an evaluation framework

The evaluation of information systems' success, such as recommender systems in e-commerce stores, has been a major challenge in information systems research because of the complexity of evaluating information systems (DeLone & McLean, 2003, p. 10). To create a solution to this problem, DeLone and McLean originally combined various success measures into one framework with six dimensions in 1992 (DeLone & McLean, 2003). It became one of the main and most influential evaluation models for information systems, like recommender systems (Wang, 2008, pp. 529–530).

In 1992, the evaluation of DeLone and McLean's work included System Quality, Information Quality, Use, User Satisfaction, Individual Impact, and Organizational Impact, aiming to have a consistent way to compare and analyze IS models and their outcomes in different academic studies (DeLone & McLean, 2003, pp. 10–11). The six dimensions that are measured in the original system are information quality (IQ), system quality (SQ), user satisfaction (US), system usage (SU), individual impact (II), and organizational impact (OI) (DeLone & McLean, 2003, p. 12).

DeLone and McLean (2003) revised their model due to important advancements in technology, especially the growth of online and e-commerce systems. (DeLone & McLean, 2003, p. 10). The model revision included three major changes. First, service quality was added due to the growing importance of support services in platform-based or outsourced services. Second, the Individual Impact and Organizational Impact were combined into one category, Net Benefits. The reason was that there were overlapping contexts in the two categories. Third, the authors maintained the Use dimension,

communicating that how much and how well a system is used reflects its success, leading to a revised model where System Quality, Information Quality, and Service Quality impact Use and User Satisfaction, which then influence Net Benefits. (DeLone & McLean, 2003, p. 22).

It is important to note that DeLone and McLean mention that the new ISSM model is great for evaluating the success of e-commerce systems, where user satisfaction and business are supported by web content, reliability, and service support (DeLone & McLean, 2003, p. 10). In the e-commerce context, Systems Quality comes from factors, like performance and reliability (DeLone & McLean, 2003, p. 24). Information Quality, on the other hand, reflects web content accuracy, completeness, and relevance on e-commerce (DeLone & McLean, 2003, p. 25). Service Quality means the overall support offered by the service provider. These are the three major qualities in an e-commerce store to define the success and effectiveness of the digital store (DeLone & McLean, 2003, p. 23). This can be seen from the updated model figure below.

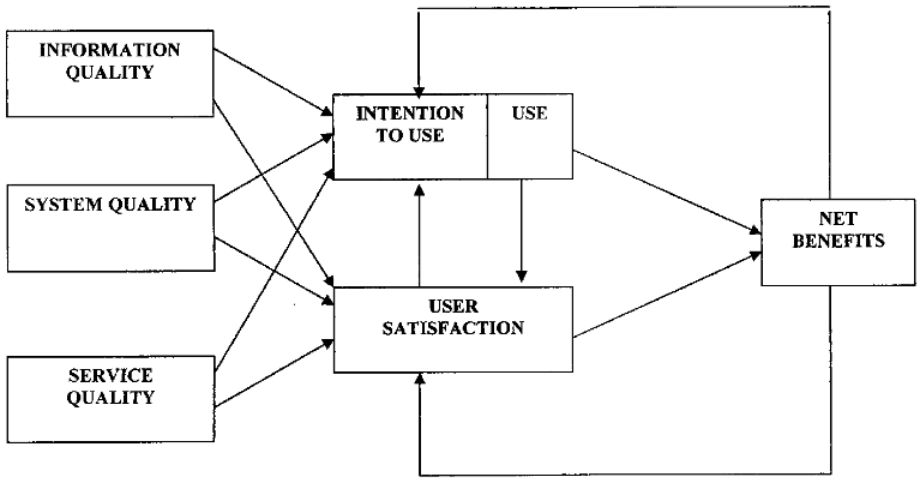

Figure 4. Updated D&M IS Success Model (DeLone & McLean, 2003, p. 24).

More recent research has also extended and validated the updated ISSM model created by DeLone & McLean for digital commerce environments. For example, Wang (2008)

suggested a redesign specifically to fit consumer e-commerce by connecting DeLone & McLean's ISSM model with technology and marketing acceptance research.

He switched the traditional Perceived Usefulness to Perceived Value, which takes into consideration both benefits and costs, and replaced System Use with Intention to Reuse, which he argues to be a more reliable measure of Net Benefits in the context of e-commerce (Wang, 2008, p. 536). His empirical findings show that System Quality, Information Quality, and Service Quality have a significant positive impact on User Satisfaction and Perceived Value, which increases the likelihood that customers return to the e-commerce platform (Wang, 2008). These findings strengthen the main structure of the updated ISSM model and validate its usage in the evaluation of digital e-commerce systems.

Even though the ISSM has been widely approved in research, it has also faced criticism. Jeyaraj published a meta-review in 2020 of 53 empirical ISSM studies, and it was found that researchers often apply only part of the model, with an average model completeness of 55% (Jeyaraj, 2020, p. 8). Another critique has been the unclear definition of Net Benefits in the ISSM. The model has been used for multiple types of users, like citizens and consumers, in different studies, which most likely means that net benefits mean different things across studies and cannot be comparable (Jeyaraj, 2020, pp. 10–11). These criticisms show that while ISSM can be used foundationally, it must be implemented with contextual awareness and carefulness.

A relevant insight by Jeyaraj (2020) shows that the ISSM model performs better in public-facing systems, like B2C e-commerce stores, compared to work systems (Jeyaraj, 2020, p. 8). This means that factors outside the model, like support from the organization, training, integration of processes, or customer knowledge, can affect results and should be considered in the analysis (Jeyaraj, 2020, pp. 7–8).

Despite the criticism, the updated ISSM has been implemented in hundreds of research works, and it remains a highly suitable and theoretically relevant framework for this thesis for multiple reasons. First, it gives a structured and highly validated approach to evaluate a recommender system's success across numerous dimensions, making sure that the separate aspects of the recommender system can be analyzed together (DeLone & McLean, 2003, p. 23). Second, the ISSM helps create a systematic structure for the design of the Analysis and Findings section of the thesis. Third, the proven adaptability of the ISSM makes it appropriate for analyzing the performance and contribution of value of a product recommender system in a B2B e-commerce store (Wang, 2008).

2.9 Summary of Theoretical Background and Literature Review

To summarize the main theoretical insights of the thesis, this section highlights key theoretical insights from the literature, research gaps that motivate this thesis, and what the literature shows is known about the thesis subject collectively. The reviewed studies show that artificial intelligence and the subfield of machine learning create the foundation for modern recommender systems (Goodfellow et al., 2016; Kaplan & Haenlein, 2019), and the literature consistently identifies three main architectures for recommender systems: Collaborative Filtering, Content-Based Filtering, and Hybrid models (Burke, 2002). Each of the recommender system types has its strengths and weaknesses, but the literature consistently suggests that hybrid models are the most suitable approach for industrial B2B product recommender systems, due to conditions that are typical in industrial B2B e-commerce, like sparse interaction data, a large number of products, and heterogeneous information sources (Zhang & Wang, 2015; Saraei et al., 2025). Prior studies also show that B2B purchasing differs fundamentally from B2C. In B2B, higher levels of transparency, contextual justification, and integration of enterprise-level data beyond transactional histories are often required, which affects the need for an aligned recommender system design (Heckel et al., 2017; Zhang & Wang, 2015).

Based on the literature, empirical evidence focusing on cross-selling performance in B2B contexts is limited, even though prior studies show that AI-driven recommender systems demonstrate positive effects on product discovery and bundling performance in e-commerce (Zhang & Wang, 2015; Kashef & Pun, 2022). On top of this, most existing studies evaluate recommender systems mainly through technical accuracy metrics, instead of organizational or managerial impact (Saraei et al., 2025). To address this limitation, prior research highlights the potential of a comprehensive evaluation framework, the Information Systems Success Model (ISSM), which evaluates the organizational net benefits of the recommender system (DeLone & McLean, 2003; Wang, 2008). However, there were no studies that have used ISSM fully to evaluate recommender systems in B2B e-commerce environments. Table 3. presents the key insights of the literature and the research gaps addressed by this thesis.

Table 3. Key insights of the literature and the research gaps addressed by this study.

Theme	**Findings based on the Literature**	**Research Gap Addressed by This Thesis**
Recommender System Models & Technical Performance	Hybrid model approaches, e.g., combining CF/CB/ARM, are proven to overcome cold-start, data sparsity and large-catalogue issues common in industrial B2B environments. Significant limitations are consistently shown in CF models, which are widely used as industry baselines.	Limited empirical research on how existing B2B recommender systems in e-commerce are designed, what constrains they have in practice, and how these limitations could be addressed with modern AI-driven approaches.
Cross-Selling as Focus	AI-driven hybrid models are superior in integrating contextual data, e.g., price, margin, product contexts, which play major roles for accurate prediction and justification in B2B transactions. The literature consistently identifies cross-selling as a key application area for B2B Recommender Systems.	There is a lack of empirical case studies focusing on measuring cross-selling performance improvement, e.g., improved product bundling metrics, within the industrial B2B e-commerce store.
Business Value Evaluation	Current B2B Recommender Systems research concentrates	There is a significant gap in research in applying holistic business value

Theme	Findings based on the Literature	Research Gap Addressed by This Thesis
	mostly on technical metrics. The ISSM gives a holistic, validated framework, addressing a crucial need for evaluating system success beyond the algorithms.	frameworks like the ISSM, which links technical quality to organizational outcomes and user adoption to evaluate the impact of AI-driven Recommender Systems in B2B e-commerce.

In conclusion, the literature demonstrates theoretical support for AI-driven, hybrid recommender systems for product recommendation in industrial B2B electronic commerce stores, while revealing gaps in empirical understanding of current system practices, cross-selling outcomes, and business value evaluation. These gaps justify an in-depth case study that focuses on existing recommender system limitations, available data resources, and organizational readiness for an improved modern recommender system. The identified gaps form the conceptual base for the empirical analysis done in the later chapter of this thesis.

3 Methodology

This chapter describes the methodological choices of this study and justifies why those methods are chosen. The methodology's main objective is to support the research of examining the limitations of the current product recommender system used in Etra Oy's B2B e-commerce store and to explore how AI-driven product recommender system approaches identified in existing research could improve product bundling performance and inform future system development. To support this research objective, this study uses a qualitative research design complemented with descriptive quantitative data. The research onion framework is used to structure the methodological choices of this study. The research onion framework gives a systematic overview of the research philosophy, approach, strategy, and data collection and analysis methods (Saunders et al., 2007, p. 132). The purpose of this framework in this thesis is to be a guiding structure, making sure that research questions, theoretical background, and empirical methods are in coherence. This study is conducted by an in-depth single case research strategy, ensuring extensive research on the issue in a real-life industrial context (Yin, 2018).

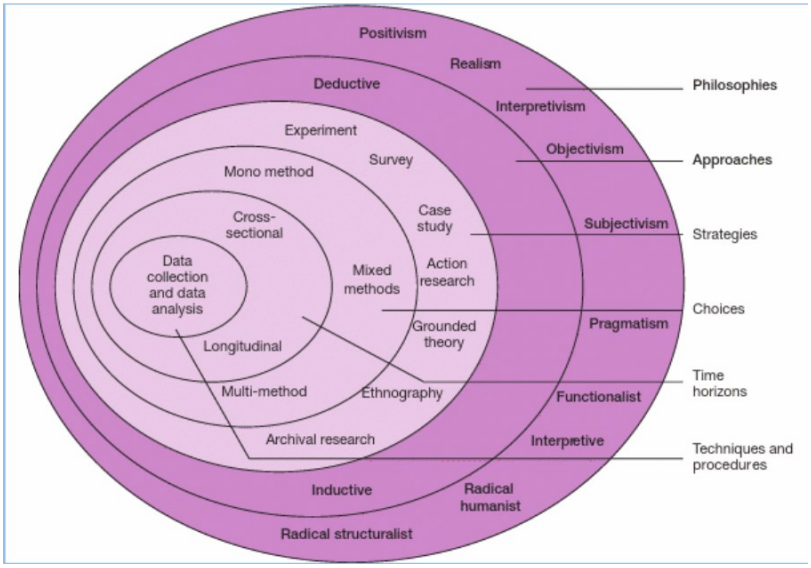

Figure 5. Research Onion (Saunders et al., 2007, p. 132).

3.1 Research Philosophy and Research Approach

This study uses a pragmatic research philosophy, which emphasizes the practical results of the research and supports the use of methods that address the research problem the best instead of sticking to a single traditional research philosophy (Saunders et al., 2007, p. 110). This makes it a great fit for this applied business research, since the aim is not only to create theoretical insights, but also to produce relevant and actionable knowledge for organizations. The pragmatic orientation is well aligned with the focus of the thesis on evaluating recommender systems from managerial and technical perspectives. The study aims to showcase how current recommender systems are perceived, designed, and evaluated in a real-world organizational context and how resources can support future system development. This is also consistent with using the Informational System Success Model as an evaluation framework, which highlights the organizational net benefits (DeLone & McLean, 2003, p. 12).

The research approach of this study is abductive. The abductive research approach is a flexible, iterative method that allows the researcher to move between existing theory and empirical observations, which allows for a deeper understanding throughout empirical research (Yin, 2018). In this approach, analyses are not a particularly linear process but recursive, as the researcher moves back and forth between the data set and the analysis (Braun & Clarke, 2006, p. 16).

In this study, the development of the interview guides was done based on the literature on recommender systems, B2B e-commerce, and the ISSM theory. The empirical findings are further used to compare and add to the current theoretical findings, especially in relation to data readiness and organizational constraints in the B2B environment. This aligns with the principle that research on managerial practice should inform derived theory, which then creates the blueprint for managerial practice (Saunders et al., 2007, p. 6).

3.2 Research Design, Case Selection, and Sampling

3.2.1 Research Design

This study is done with a qualitative, single-case study design. Yin (2018) describes that case study research is appropriate when the research seeks to answer “why” and “how” questions, and when the researched phenomenon is within a real-life context. Due to the exploratory nature of this study and the limited empirical evidence on B2B recommender systems evaluated holistically from the business perspective, an in-depth case study gives a nuanced understanding, which can be otherwise difficult to achieve, for example, with quantitative methods (Flyvbjerg, 2006; Yin, 2018).

This aligns with Stake's (1995) interpretive, instrumental case study approach, in which the case organization is not researched for its own sake but with the aim of developing an in-depth understanding of AI-based recommender systems in a B2B e-commerce context. The study emphasizes organizational context and multiple stakeholder perspectives, reflecting that the system value and usefulness come from practical use within the organizational setting rather than through causal explanation.

A qualitative approach is therefore used to capture nuanced and in-depth answers to organizational practices and to give detailed insights into system limitations and processes. Quantitative data is used as supportive material to complement qualitative findings and to give descriptive insights into the organization’s data quality and availability.

3.2.2 Case Selection

Etra Oy is selected as the case organization for this research. Etra Oy is a Finnish technical sales specialist that provides a comprehensive range of industrial products and services, serving as a trustworthy partner for customers in various industrial sectors, operating an e-commerce store (Etra Oy, n.d.). The case company was selected by its relevance to the research topic and the willingness of the organization to provide access to relevant

stakeholders and data sources, which were critical for conducting this single case research. Additionally, Etra Oy is a member of Technology Industries of Finland (TIF), which provided the researcher with a research grant. The study's focus on depth instead of broad scale, justifies the single case study selection. Flyvbjerg (2006) argues that carefully selected single case studies can create valuable insights and challenge previous assumptions, especially when the goal of the research is analytical instead of statistical generalization.

3.2.3 Sampling

The qualitative data in this thesis are collected using purposive sampling, which allows for the selection of interviewees based on their readiness to answer the interview questions (Saunders et al., 2007, p. 230). Interview participants were selected based on the employees' roles and responsibilities at the company. More in-depth, a heterogeneous purposive sampling method ensures that all the data collected is relevant to the research question and that data is collected from multiple organizational personnel with different perspectives (Saunders et al., 2007, p. 232).

3.2.4 Participants of the Interview

Each of the participants was invited via email to be part of this study. Each participant is an employee of the case company, and their work is relevant to give in-depth information to support the objective of this study. The interviewed participants will remain anonymous, but their current titles at the company are shared, as it is essential information for understanding the context of the qualitative analysis and will support the analysis of the findings. The participants are recorded in a randomized order in table 4. below.

Table 4. The participants of the interviews

Participant	Title at the case company
A	Marketing Manager
B	Data Specialist
C	Director of Sales
D	ICT and Development Director
E	Purchasing Director
F	E-Commerce and PIM Manager

3.3 Data collection methods

3.3.1 Qualitative data collection

Qualitative data were collected through semi-structured interviews with the organization's stakeholders. This data collection method was selected because it gives the researcher the possibility to have a list of themes and questions to cover while having the flexibility to add or exclude questions based on the interview (Saunders et al., 2007, p. 312). The interview guides were created based on the literature review, research questions, the organization's data, and the role of the interviewees. This method allows the participants to give in-depth answers and describe their experiences while allowing the researcher to keep the data collection in the desired themes. Saunders et al. (2007, p. 312) explain that semi-structured interviews are suitable for complex organizational phenomena, in which the questions are open-ended, and the logic of the questions may be varied.

Four of the six interviews were conducted in English, and two were conducted in Finnish at the interviewee's request to ensure accurate communication during the interview. The interviews held in Finnish were translated into English by the researcher for analysis and reporting purposes. The researcher is a native Finnish speaker, and the translations aim to match the original meaning of the interviewee's responses. However, it should be acknowledged that minor interpretation differences may arise from translations of the responses.

3.3.2 Quantitative data collection

Quantitative data was collected from Google Analytics and Click Sense Sales data through the organization's internal systems. These data sources give information on what data is available for the organization to use, descriptive information on webshop user behaviour, product categories, sales performance, and funnels. The quantitative data collection's purpose is to assess data availability, structure, and usability in the future recommender system, not to perform hypothesis tests. Quantitative data is not used as a primary analytical basis, but rather to complement the qualitative findings and to deepen the recommendations.

3.4 Data analysis methods

3.4.1 Qualitative data analysis

Thematic analysis was used to analyze the qualitative data. Thematic analysis gives a systematic way to identify, analyze, and report patterns in the qualitative data (Braun & Clarke, 2006, p. 6). The themes were selected using deductive logic, based on the theoretical research, as well as inductive logic, where themes are linked to the data. This allows the analysis to stay theoretically grounded while staying flexible for empirical findings (Braun & Clarke, 2006, p. 12).

3.4.2 Quantitative data analysis

Descriptive methods were used to analyze the quantitative data in this thesis. The analysis was done to support the qualitative findings and to evaluate the feasibility of different recommender systems for the organization.

3.5 Research quality, Reflexivity, and Limitations

3.5.1 Research quality

The research quality is taken into consideration through focusing on credibility, transferability, dependability, and confirmability, which are criteria for qualitative research (Lincoln & Guba, 1985). This study aims for credibility through conducting semi-structured interviews with multiple stakeholders representing different perspectives, and having interview guides designed based on theory and prior literature review. Transferability is addressed by giving a comprehensive description of the organization's context, allowing others to evaluate the applicability of the findings in similar cases. Dependability and confirmability have been taken into consideration by a transparent and systematic research process in data collection and analysis, in addition to considering reflexivity and potential researcher biases.

3.5.2 Reflexivity

The researcher recognized the active role as a researcher with prior knowledge and assumptions, which may create unintended biases. The researcher has also been personally in touch many times with the organization’s employees, for whom the thesis is conducted for. Technology Industries of Finland Centennial Foundation has given a grant to the researcher with the requirement of the thesis being an AI-related master’s thesis project done for one of the foundation’s member companies, in this case, Etra Oy. The purpose of the Foundation is “to develop competences and an innovative business environment for the companies represented by the Federation of Finnish Technology Industries” (Technology Industries of Finland Centennial Foundation, n.d.). The researcher acknowledges that this may have some unintended effects on the research. To mitigate the biases, this study employs a systematic approach including a structured interview

guide, theory-driven analysis, and transparent reporting on the methodological decisions and findings (Saunders et al., 2007).

3.5.3 Limitations

The findings of this thesis are not statistically generalizable since this research is a single case study. Additionally, the analysis focuses on data availability and organizational readiness, instead of technically implementing or testing recommender systems. These limitations are intrinsic in the chosen research design and are intentional choices supporting this study's goals with limited resources.

4 Analysis and Findings

In this chapter, the results of the research findings are presented in a structure that follows the ISSM framework, which is used as a fundamental part in the literature review of this paper. All the findings presented in this study are reported to support the study's aim, which is to examine the limitations of the current product recommender system used in Etra Oy's B2B e-commerce store and to explore how AI-driven product recommender system approaches identified in existing research could improve product bundling performance and inform future system development.

The findings are mainly based on the interviews with the case company's employees, but also descriptive data analyses of the case company's quantitative data are integrated into the findings in a supportive role to give more comprehensive findings. Since the interviews were semi-structured, pre-structured interview guides were used to get information related to key themes of this study, which helped answer the research questions. Structuring this chapter based on the ISSM framework, including System Quality, Information Quality, Service Quality, Use, User Satisfaction, and Net Benefits, ensures that the findings are organized to support the study's objective and to identify the common patterns and opposing perspectives from the data.

The research interviews with the case company's employees played a crucial role in this study, as the researcher considers that open discussions with stakeholders from different perspectives and areas of expertise were required to get in-depth data to support this study's objective and to get data to support the key themes.

In this chapter, the findings are analyzed in detail to give insights to help answer the research problem. Throughout this chapter, quotations of the interviewed participants are included to reflect the authentic information from the interviewees. The participants are referred to by their assigned letters presented in Table 4. to keep anonymity.

4.1 Case Context: Etra Oy and Webshop Environment

Etra Oy is a Finnish technical sales specialist that provides a comprehensive range of industrial products and services, serving as a trustworthy partner for customers in various industrial sectors. The company was established in 2007 through a merger of multiple Finnish companies and is part of the Etola Group, which is a family-owned Finnish company (Etra Oy, n.d.). In 2024, Etra Oy achieved a revenue of 330,0 million euros, with a profit of 34,9 million euros (Finder, n.d.). The company employs over 850 people and operates nationally through more than 45 physical stores across Finland and internationally in the Baltic countries and Scandinavia. Etra Oy has four core values: reliability, high quality, service, and sustainable development, which guide the organization's operations (Etra Oy, n.d.).

Etra Oy operates a B2B e-commerce store alongside the physical stores. The E-Commerce and PIM Manager mentioned that the company's webshop functions as a critical sales channel for the company, and at the time of the interviews, approximately six percent of the company's total sales came from the webshop, and the share of webshop sales has been growing steadily over the recent years (F). At the case company, the webshop has a dual purpose, functioning as a direct purchasing channel and information resource for customers, and for internal employees, it serves as a daily tool for searching product specifications and presenting products to customers (D). This dual role makes it strategically important for both electronic and in-person sales.

Currently, Etra's webshop uses a rule-based product recommender system, where product relationships are defined manually by product managers, and supported by supplier-provided data and co-purchasing analysis. The current recommender system displays two types of recommendations: exact-match items, such as spare parts that are directly compatible with a specific product, and related items, which give more room to decide what is shown in the recommendations, such as complementary accessories or supplies that the product managers select based on their expertise (F). The E-Commerce and PIM Manager also described that at the time of the interview, recommendations were available for approximately 60,000 items of the little bit over 180,000 products available in

Etra Oy's e-commerce store, and that the current recommender system does not utilize personalization or behavioral data (F). The following sub-sections examine the system's design, limitations, and organizational context in more in-depth, structured around the six dimensions of the Information Systems Success Model.

4.2 Data availability assessment, Quantitative section

This subsection presents an overview of the currently available quantitative data sources at the case company to help assess the fit of data-driven recommender systems and to support the qualitative findings. The data was extracted by a case company's employee from internal data sources, QlikSense, and Google Analytics, which was then shared with the researcher for analysis purposes. These data sources include sales transactions and webshop browsing data.

The sales transaction data covers 306 product groups across 26 parent categories and includes order values, order counts, order lines, unique customer IDs, and the webshop's percentage share of total sales for each product group. The data is split between all sales channels and webshop sales, which makes it possible to evaluate how much of each product category's sales come from the webshop compared to other sales channels. The marketing manager noted in the interview that the case company has substantial data available, which is not leveraged for product recommendations currently. She mentioned: "We have incredibly good data in both Google Analytics and our sales systems, but we haven't put it to use for this kind of product planning" (A).

In addition to the sales data, the company has webshop browsing data available, which tracks page views at the product group and item level, total views, views linked to identified customer accounts, and unique visitor counts. The dataset also has a page-level navigation data covering over 238,000 unique URLs, showing which parts of the webshop get the most traffic, including product category pages, product item level pages, shopping cart, and checkout page. The e-commerce and PIM manager identified specific data

sources that could be utilized for recommender systems but are currently not used at the case company. He described "product views, comparison rates, those are basically very easy" input to obtain (F). He additionally pointed out that customer group data, such as analyzing what other companies within the same industry have purchased, as a potential data source for improving recommendations (F). However, the browsing data may not provide a full representation of all webshop activity due to customer cookie opt-outs. The data also shows that browsing data and purchasing behavior can be linked at the customer level. This means that the case company is able to analyze which product categories a specific customer browses and purchases.

In summary, the case company has access to multiple data sources to utilize for the recommender system, such as sales transaction data, customer identification data, and browsing behavior. The following sections examine the current recommender system and its limitations through the ISSM framework, which is structured with six dimensions.

4.3 System Quality: Technical Functionality and Limitations

In the Information System Success Model (ISSM), system quality includes the functional and technical characteristics of the system. This includes things like system architecture, reliability, and scalability of the system (DeLone & McLean, 2003). The system quality in the B2B e-commerce recommender system is critical, since it determines whether the product recommendations are delivered, and how accurately and scalable the system can create cross-selling opportunities.

The interviews showed that the current recommender system at Etra is a rule-based and largely manual architecture, in which the relationships between products are defined based on suppliers' provided data, product managers' decisions, and historical purchase data. Even though the current system gives a functional baseline, it comes with constraints in scalability and adaptiveness regarding cross-selling.

The interviewees systematically described the company's current product recommender system as functional operationally, but with structural limitations. Due to these structural limitations, the recommender functions more as a static support tool than a continuously learning dynamic system.

The subsections below present the key findings related to structural constraints of the current product recommender system, the system's scalability and requirements, which were identified in the empirical data.

4.3.1 Manual, Rule-Based System Limits Adaptability

The findings show that the current product recommender system at Etra is manual and has a rule-based architecture, in which the relationships between products are defined by the employees instead of being generated with the help of machine learning. The system's design and characteristics have a direct impact on the adaptability of the system.

The interviewees consistently described the recommendation logic as based on product managers' manual curation, in some cases supported by data provided by suppliers. The Purchasing Director explained that "related and substitute products are added based on recommendations from our product managers mainly. We also use supplier provided data, but... we need to do this job by ourselves" (E). The E-Commerce and PIM Manager similarly emphasized the manual nature of the process, noting that "at the moment it's totally manual. Our product manager made the decision… he has to know the product and he makes the human design decision what he will show" (F). Currently, product recommendations are not generated automatically but rely on employees' expertise and decision-making. As a result, the system cannot adapt to changing customer needs, and the quality of the recommendations depends on organizational resources rather than on automated processes.

In some cases, supplier data supports the relationship definition, although the final recommendation decision remains with the product managers. The E-Commerce and PIM Manager clarified the role of suppliers in this process: "it's manual, but in real life at least half of those are something that we receive from our supplier. We ask them that if you are selling this item, please tell us what items are related with this one. And that's the main source" (F). This affirms the dependency on human decision-making in the system, with supplier input serving as a starting point rather than as an automated data feed.

In addition, the system logic is static and does not use browsing behaviour, purchase patterns, or user interactions to generate recommendations. The Marketing Manager confirmed that "no, there is no personalization at the moment" (A), and the E-Commerce and PIM Manager further explained the underlying tracking limitation: "there ain't any way at the moment... that we can actually track the recommender data... what is really clicked and bought with the item" (F). Based on these findings, there is currently no personalization or behavioural learning used within the system, which reinforces the static nature of the current rule-based approach.

4.3.2 Limited Coverage Restricts Cross-Selling Potential

The findings show that there is limited coverage of product recommendations at the webshop, which limits its ability to provide consistent cross-selling. A key finding revealed that product recommendations are available for only around one-third of the products in the webshop, leaving a large percentage of items without any cross-selling opportunities through product recommendations.

The E-Commerce and PIM Manager quantified the scale of the catalogue and the current coverage, noting that there is "a little bit over 180,000... and recommendations we have on about 60,000 products at the moment" (F). He further identified this as the central limitation of the system: "biggest problem is we don't have enough those recommendations… almost 60% product without any recommendations" (F).

This lack of recommendation distribution results in users frequently encountering products without product suggestions and having an inconsistent recommendation experience across the webshop. The limited coverage leads to the system not functioning reliably in cross-selling across the webshop.

4.3.3 Visibility Constraints Reduce System Usage

Participants highlighted that the visibility of the recommended products is restricted by the company's decision to only be shown at the group product level and individual product pages. The E-Commerce and PIM Manager described this placement directly, explaining that recommendations are placed "on the group product level and single product level. So basically customer has to go through the product tree or use the search function... when he is in the product level, he can see what recommendations we have" (F). This placement restricts the recommendations to be seen throughout the whole customer journey, relying on user navigation rather than providing continuous proactive recommendations throughout the whole customer journey. As a result, this reduces the likelihood of influencing the purchasing decisions of recommended items since recommendations are visible only when customers browse specific products. The same participant also explained: "We don't do recommendations on the shopping basket or in the checkout page" (F).

From the System Quality perspective, not showing recommendations in all transaction stages, such as the shopping cart and checkout page, limits the visibility of the recommendations.

4.3.4 Accuracy Sensitivity Shapes System Design in B2B

The participants in unison brought up a point that high accuracy is critical in the case of the company's product recommendations, which affects the system design. In the B2B environment, trust is important, and the recommendations have to be consistently reliable, since incorrect suggestions can be costly or lead to major consequences for the customers. This requirement is a significant difference between B2C and B2B settings, where typically the recommendations can rely on approximate matching.

The ICT and Development Director captured this concern directly, by saying that "The accuracy must be near to 100%… when the customer purchases wrong product the whole trust is gone… might be gone in one occasion" (D). He further added "We have to be sure the product actually fits... we cannot do mistakes in that field and that's why it's so important to do that manually" (D).

This has resulted in relying on the manual creation and validation of product recommendations to ensure the correctness of the recommendations. Overall, the findings demonstrate that the high accuracy needs for the recommender system in the B2B context constrain the current system architecture, and that the highly accurate options are superior, such as manually verified recommendations.

4.4 Information Quality: Product Data and Recommendation Logic

In the Information Systems Success Model (ISSM), Information Quality includes data's accuracy, consistency, relevance, and completeness used by the system (DeLone & McLean, 2003). The information quality in the B2B e-commerce recommender system significantly affects how successfully the product recommendations can reflect to the customer needs and support cross-selling. This chapter presents three subsections presenting the key findings related to information quality, including variability and

inconsistency in supplier-provided product data, structural limitations in product attribute standardization, and the quality and consistency of product relationship data.

4.4.1 Variability and Inconsistency in Product Data

The findings show that product data gives a foundation for creating product recommendations, although there are inconsistencies in data between suppliers, product categories, and completeness, which reduces its reliability. Etra's product data is dependent on the information provided by the suppliers, resulting in differences in data quality across product categories.

Variability between the supplier-provided data appears as a significant reason for inconsistencies in Etra's product data. The participants shared that Etra receives the data from suppliers, ranging from receiving it in structured imports to just receiving the information via email. The Purchasing Director described the following: "I could say that it's semi structured... somebody is just sending by e-mail... there is some differences but most of them comes quite structured" (E).

On top of that, there are differences in reporting standards, like the number of decimals, which can limit the comparability of products. The Data Specialist noted that "different suppliers, they might be using a different standard of reporting... they might be using a different set of like different number of decimals for measurement" (B).

Additionally, data quality varies across products due to differences in regulatory requirements and how dynamic the product is. Highly standardized or regulated products, like chemicals, seem to have more complete and structured data since the mandatory documentation is required. One participant said: "standardized products are easier [to provide structured product information than other categories] … because of the legal regulation" (E).

On the other hand, dynamic product categories require regular data updating, which can reduce the completeness and consistency of the data, as one interviewee said:
“Even the categories are different in how dynamic the items are. Like for clothing... you have to constantly be adding new items and adding the information there instead of having the same five items for 10 years” (B).

The E-commerce and PIM manager summarized the situation: “There is really big variation between different product groups and different product managers even. But in overall, I think that it could be so much better” (F). This uneven data quality can lead to inconsistent recommendation performance across product categories and reduce the overall effectiveness of the system.

4.4.2 Product Attribute Structure and Standardization

As the previous subsection showed that the supplier provided data differs a lot, this subsection addresses a related problem to it. When data is available, it is often structured in a hard to utilize form for the automated recommender logic. The issue in this is that, if the system uses the product information in the recommendations, then the system needs to be able to read and act upon that data.

Findings show that technically relevant product information is sometimes written in a free-text field instead of a discrete attribute that is easy for the machine to read. A participant demonstrated this concretely: “screws, for example... I don't think we have good data on how many screws are in one package. It is written, you can find it from the technical name of the item, but even that it's not really machine friendly” (B). The organization has recognized this problem and has thought about different ways to enrich the product data in a structured way.

Also, the numerical data lacks standardization between suppliers' given data. The same measurements in Etra's data can appear with different decimals depending on the source, which can affect the filtering logic. The Data Specialist described the issue: "when you're trying to use a filter, you might have one centimeter and 1.0 centimeter and 1.00 centimeters. So it needs to be standardized to be actually really useful" (B). She also mentioned that this same problem extends to qualitative attributes as well, where suppliers can describe the same thing in different words, which makes the products hard to compare: "a slight variation on how you decide to standardize your items, it makes them non-comparable to each other even if they are the same thing" (B).

Another key finding regarding data structure is that the current product categorization was built for internal ERP logic and for internal use instead of for the customer journey. Interviewee brought up that: "some of those [groupings] are not optimal for web shop. They've mostly been designed for internal use, not for web shop use" (B). These limitations have been noticed in practice by previous case company's test, where the automated recommender system failed to give relevant recommendations. The E-Commerce and PIM Manager described that: "we have tested in the past like what kind of recommendations the ElasticSearch... could give... The results were so far away from the product... [or] show the next size of hand clothes... I don't believe that the customer just want to see that kind of items" (F).

These findings reflect the data's completeness and consistency dimensions of the information quality of the ISSM framework identified by DeLone and McLean (2003), suggesting that structural data is a critical part for effective recommendation logic.

4.4.3 Product Relationships and Cross-Selling Logic

The findings in this section focus on the quality of the product recommendations in the B2B webshop. Since the previous subsection addresses the key limitations in the product data, this subsection showcases findings related to the quality of the currently available product recommendations.

Despite the limited coverage of product recommendations, the interviewees stated that there have not been any complaints from the customers about the quality of the current product recommendations. When asked about the accuracy of the current product recommendations, the Director of Sales stated that "it has never come across that there would be a completely wrong product or a completely unrelated product there in the product recommendations" (C). The ICT and Development Director similarly confirmed this, noting that "I haven't heard that there have been mistakes in our related products" (D).

These findings of having no customer complaints show that the manually created recommendations, while limited in coverage and consistency, have been relevant based on the stakeholders' direct and customers' indirect feedback. This indicates that involving the employee's expertise in the product recommendations produces meaningful and relevant outputs, although this process is limited in scalability. However, it is worth mentioning that the perceived quality of the recommendations from customers is based on the lack of negative feedback, instead of systematic feedback collection from customers.

4.5 Service Quality: Organizational Support and Governance

In the revised Information Systems Success Model, the service quality refers to the overall support offered by the service provider (DeLone & McLean, 2003, p. 25). In the B2B e-commerce context in this thesis, service quality demonstrates how the organization maintains, develops, and governs the recommender system. The service quality section

is divided into three subsections addressing the organizational structure behind the recommender system, the process constraints limiting its development, and the boundaries given by the organizational leadership.

4.5.1 Organizational Structure and Coordination

The findings reveal that the development and maintenance of the recommender system at the case company is done by a small internal team. A participant describes the team: “we have a certain team for e-commerce functions, and we are taking care of those main things related to e-commerce with four people” (D).

While this team is responsible for the e-commerce functions, the product relations work is distributed across 20 to 30 product managers, who create recommendations for the products alongside their other responsibilities. There is a cross-functional group that does the cross-product relation work, reviewing product relations and talking about the priorities related to that. An interviewee described that: “it is done together with the PIM team and e-commerce team and product managers. So, we have a small group collected from them" (E). Even though the work is distributed, it was clear that the e-commerce team is the responsible owner of the webshop, its recommender system, and its functionality. When asked whether ownership is clear or fragmented, the Purchasing Director confirmed that: "from my point of view, yes, it's clear," identifying the e-commerce team as the responsible owner (E). While there is a clear ownership, practical capacity remains a constraint because of the limited size of the team and the product managers' competing responsibilities.

4.5.2 Manual Process and Resource Constraints

From the interviews, the most consistent findings related to service quality were that the recommendation creation process is manual and there are not enough resources to sustain it. The constraint was described from multiple angles by the interviewees.

When interviewees were asked about the process of creating these recommendations and if there is a standardized process of creating product recommendations, participants answered that there is no standardized process. The Purchasing Director replied simply: “unfortunately, no” (E). The E-Commerce and PIM Manager explained: “at the moment it's totally manual. Our product manager made the decision... He has a limited knowledge of all of our products, and he sees only his products” (F).

As a result, the individual dependency without standardized logic leads to significant variations in relationships across the items at the webshop. This means that the lack of a standardized process makes the recommendation creation depend on product managers' individual effort and knowledge, rather than an organizational-level standardized process.

Findings show that another challenge in this process is the scale of the task in creating and updating product recommendations and product information. The E-Commerce and PIM Manager described that the current system cannot support the pace of growth in product assortment: “If we opened like last year like 67,000 new item codes… that’s a lot of recommendations… and they [product managers] don't have the time… it's just not working with that amount of products” (F). Also, the Purchasing Director and ICT and Development Director noted the same issue as significant. The Purchasing Director said that: “this [handling product information] needs quite much resources from our product managers and sometimes it is a bottleneck” (E). On top of that, the ICT and Development Director added: “I would say that the manual work and the number of products it might be the biggest challenge... our product managers don't have the time to do that as good as it will be required if we want to improve” (D).

Having the same problem identified from multiple perspectives within the company shows that manual processes and non-systematic logic in information updating and product recommendation creation is hindering the recommender system's scalability and ability to provide consistent cross-selling opportunities.

The e-commerce and PIM manager identified three main bottlenecks in adding more recommendations to the webshop: first is difficulty in acquiring cross-selling data from suppliers, where in some cases it had taken over a year to reach the correct contact person; second is the inefficiency of the manual process itself; and third the lack of technical capability to automate the process (F). Similarly, the purchasing director said that the "more automation between suppliers and our PIM system" (E) is the biggest bottleneck in maintaining the product data quality and product relations.

These findings overall show that service quality's limitations come from resource and manual process constraints, not from unclear ownership and organizational intent.

4.5.3 Ownership Governance and Development Boundaries

A significant finding related to service quality is the role of company values and family ownership structure in defining the boundaries for the product recommender system. Both the e-commerce and PIM manager, as well as the ICT and development director, described that the owners of Etra had decided not to show product recommendations on the shopping cart or the checkout page. An interviewee mentioned that:

> *we don't do any after sales recommendations and we don't do recommendations on the shopping basket or in the checkout page. Both of those are guidelines come from the owner of the company. They wish that the purchase process is simplified* (F).

The reason behind this was further contextualized by another participant saying that the company's values are driving the decisions: "we don't want to be classical B to C web-shop... we want to be like B to B... professional company" (D). This shows that as a family-owned company, the owners directly shape the decision-making and that the company's values drive decision-making also in the development of a recommender system.

Similarly, the marketing manager emphasized that value-driven governance, with trust and reliability as core values of the organization, should shape the recommender system design, and that the organization prioritizes providing genuine value to the customer rather than being perceived as commercially pushing (A).

The absence of product recommendations performance tracking data limits the ability of the e-commerce team to advocate for recommender systems' development. Participant said that: "we don't have the correct way to promote this internally that, hey, we are actually doing this, we can get the money from it" (F). With no measurable evidence on the system's impact, it makes it difficult to get the organization's support for a larger investment.

Service quality influences both the use and user satisfaction of the system (DeLone & McLean, 2003). These findings show that an organization's ability to support the recommender system affects how effectively the recommender system can perform, making service quality an important factor in the product recommender system's success in the B2B e-commerce context.

4.6 Use: How Recommendations Are Used in Practice

In the revised Information Systems Success Model, the Use dimension communicates that how much and how well a system is utilized reflects its success, and that System

Quality, Information Quality, and Service Quality impact Use (DeLone & McLean, 2003, p. 22). In this thesis, in the B2B e-commerce context, it means who uses the system, in what situations the system is used, and what role product recommendations have in the purchasing process in practice. This chapter is divided into three subsections: first, the dual-purpose use of Etra's webshop by customers and internal employees; second, where recommendations have the most potential based on customers' purchasing patterns; and third, the supporting role of recommendations in the purchasing process, which is still mostly done through human interaction.

4.6.1 The Webshop's Dual Role

The interviews pointed out that the webshop and its product recommendations are used both by customers and internal employees. For the customers, the webshop is used both as a direct purchasing channel as well as to find product information and to compare products. On the other hand, the findings show that the webshop is an important internal sales tool for the salespeople, which they use on a daily basis. The dual-purpose of the webshop and the product recommendations push the webshop beyond the traditional e-commerce usage and make it strategically important in both electronic and in-person sales processes. An interviewee described: "Etra website is one of the most important tools for our salesperson personnel because they are searching our product information and information of our products from there and it's like also guide for them as well" (D).

The reason for internal use is explained due to the scale of the product range at Etra. Multiple interviewees mentioned the importance of the webshop in sales. The ICT and Development Director mentioned: "We have over 300,000 products. No salesperson can be an expert in everything. You very often see in our stores that products are presented from the webshop and detailed specifications and dimensions are searched from there" (D). The marketing manager also stated this by describing the webshop as functioning

like "one extra salesperson for the sales staff” (A). This shows that webshop is a centralized knowledge base tool that supports sales personnel in giving accurate and detailed product information to customers.

In addition, the findings show that product recommendations play a role in internal use by the salespeople, providing ideas of what additional products can be sold during live customer interaction. As one interviewee said: “Our own people use it for the product information, and for them the recommender is also important because they can get the impulse to what they can sell with the product if the customer is in the store visiting live within the store” (F). This suggests that product recommendations can indirectly affect cross-selling by helping internal salespeople choose relevant cross-selling opportunities.

However, the Director of Sales described the internal use of product recommendations as supportive rather than a reminder to salespeople that complementary items are not overlooked. In the interview, he said: “These are mostly things that our salespeople already know, but they work as a good reminder to make sure that complementary items are not overlooked” (C). This indicates that the recommendations are in a secondary role to the sales personnel’s existing knowledge and expertise.

These findings indicate that in this case of the B2B e-commerce context, the recommender system plays a wider role than the traditional customer-facing function, working also as a tool for internal sales operations.

4.6.2 How Purchasing Context Shapes Recommendation Use

One finding based on the interviews is that the use of webshop and the product recommendations varies depending on the purchasing context, based on the product type, and customer profile. The findings show that the recommendations are potentially more relevant and useful in specific types of purchasing situations.

Based on the interviewees, the routine and standardized purchases are often done through a webshop, using it as a direct purchasing channel, with limited need for recommended items since the customers' needs are predefined and the familiarity of products is high. An interviewee said: "one area where you see a lot of webshop purchasing is standardized products… a standardized product that the customer repeatedly needs... then they easily turn to the webshop" (C).

In contrast, when buying special products, where technical requirements are uncertain, the webshop and its recommendations are often bypassed completely, and customers interact directly with salespeople. As mentioned in the interview: "when something special is needed, some one-time purchase… then they [customers] very often turn to the salesperson" (C). That reflects the technical nature of Etra's business as a B2B webshop, in which selling the correct product to customers' needs is critical.

Findings show that there are also situations where the customers search for products, compare options, and evaluate which solution would be the best for them, and for that, product recommendations appear relevant. In these situations, recommendations can work as reminders or help customers to find complementary products that might otherwise not be seen. The marketing manager shared her perspective on these types of recommendations in the interview that customers might "get the impulse that it's good that Etra reminded me… that I also needed this lubrication with the bearing" (A).

On top of this, the findings showed that usage patterns vary across customer profiles. An interviewee summarized that large industrial customers tend to use the webshop for purchasing standardized categories, where smaller or digitally oriented customers rely on the webshop for a broader variety of purchases (D). The findings also show that long-term customers tend to use the webshop more for direct purchasing, and newer customers use it mainly to search for information (C). Additionally, a participant explained that the geographical location of the customer affects the webshop use, as customers

located far from Etra's physical store, or in areas where there is a lot of traffic, rely more on the webshop and its product recommendations due to having less direct sales support (F).

4.6.3 Recommendations as supporting signals in the purchasing process

Based on the findings, the product recommendations currently play a supportive role rather than a driving role in the purchasing process at Etra's webshop. The customers tend not to search for recommendations, but they encounter them passively when navigating through the webshop. An interviewee describes that recommendations are visible only on the product level and single product level on the webshop (F), meaning that interactions with the recommended products rely on prior product search instead of intentional engagement throughout the webshop use.

On the other hand, the director of sales noted that it is reactive purchasing behaviour from Etra's customers when buying complementary products (C), indicating that customers react to the recommendations when they are presented. This means that the product recommendations do not initiate the purchase decision, but try to influence the customer to buy additional products when the customer is already on the product level and single product level sites.

Regardless, the human interaction remains significant in the purchasing process. Findings show that customers often rely on salespeople for guidance, emphasizing the human communication in decision-making. As the interviewee mentioned: "they [customers] contact our salespeople a lot… they definitely ask the seller" (C). At the moment, salespeople heavily rely on their own expertise when suggesting complementary products, and webshop recommendations often function as a secondary aid for them. The director of sales explained that complementary products are mostly already known to our salespeople, but product recommendations function as good reminders (C).

The interviewees explained that more extensive recommendations coverage would benefit customers. However, the actual impact of the product recommendations cannot be measured directly at the moment at Etra, since no tracking data exists to show how recommendations influence purchasing behaviour. The findings overall show that recommendation use in the case company's B2B webshop is context-dependent and primarily serves as a supportive function to purchasing decisions.

4.7 User Satisfaction: Customer Perception and Experience

In the ISSM framework, user satisfaction reflects the perceived value of the system's output (DeLone & McLean, 2003). In this case, user satisfaction is evaluated based on the internal stakeholders' perspective, including their observations of customer behaviour. System quality, information quality, and service quality affect user satisfaction (DeLone & McLean, 2003). This section of the thesis focuses on how users perceive the recommender system's usefulness, the role of trust in user satisfaction in the B2B context, and what things are currently limiting user satisfaction.

4.7.1 Perceived Usefulness of Recommendations

The findings suggest that, when product recommendations are available in the webshop, they are perceived as useful based on the internal stakeholders' opinions and observations. Multiple interviewees described positive experiences with the current recommendations. As an example, the marketing manager described that both salespeople and customers have given positive feedback on the current product recommendations, commenting that the recommendations help users remember complementary items that could be otherwise forgotten:

> *They help to remember if you've bought for example a vacuum cleaner, you remember to buy the dust bags. Or with very technical products where you should remember to buy a specific attachment, then they are there at the bottom and you get everything in one order* (A).

Likewise, the ICT and development director pointed out that having related items visible at the webshop is important on multiple levels of the business. He said: “It’s very important to have these related products on the product side… because we are a technical sales company, it’s important to help customers find the right product for the right use” (D).

Based on these findings, for existing recommendations user satisfaction is positive, driven by their functional usefulness rather than by advanced personalization or proactive product discovery. The current recommendations bring value to the users because they reduce the risk of incomplete purchases and support efficient purchasing, which aligns with the B2B purchasing priorities.

4.7.2 Trust and Reliability of Recommendations in the B2B

Findings indicate that user satisfaction with the product recommendations in the B2B webshop context is tied to trust and reliability. Interviewees said that in Etra’s case, the customers have not questioned the accuracy of existing recommendations. A participant said: “I don't believe that customers doubt the existing product recommendations. It's more the lack of product recommendations” (C). This suggests that the customers seem satisfied with the current recommendations, and that the satisfaction with recommendations' quality is not currently a concern.

Also, the interviewees explained that less targeted recommendations could negatively affect customers' trust. The marketing manager raised a concern in the interview that if

recommendations were irrelevant products across irrelevant categories, it could hinder the professional image of the webshop. The interviewee stated:

> *I just want to ensure that it doesn't recommend just anything at random cross-wise, so that if a person is looking at a bearing and a bearing lubrication unit, it then suggests, 'here is a coffee package and green marbles' [food products] for you. I'm not sure if that would turn against us* (A).

She further described that trust and reliability are core values of the organization, and the recommendation system should be aligned with that, instead of showing irrelevant products. Based on these findings, in the B2B context, user satisfaction is shaped a lot by the perceived reliability of suggestions shown.

4.7.3 Satisfaction constrained by incomplete coverage

The previous subsection showed that existing recommendations are perceived as useful, however the findings indicate that the lack of recommendation coverage in the webshop limits user satisfaction. The key finding is that dissatisfaction is not driven by the quality of the recommendations, but by the fact that many products lack recommendations completely.

Findings show that customers have given feedback of wanting more recommendations. The director of sales explained that customers have given negative feedback regarding the lack of recommendations. He noted: "in a negative sense, yes... they [customers] would wish for more of it [recommendations]" (C). He further explained that customers have been asking for more information about substitute and alternative products that could help them with cost savings. This shows that the customers see the value of the recommendations and want the coverage to be expanded.

Another interviewee also described a similar pattern from the company's internal feedback about product recommendations coverage in Etra's webshop:

> *The amount of recommendation has been probably more than doubled in one year and two years ago. When we discussed this a lot with our salesperson, the feedback was that there ain't enough recommendation or a recommendation is always missing* (F).

This suggests that the coverage of recommendations is a limitation of user satisfaction both from the salespeople's and customers' perspectives, and that expanding the coverage would improve the recommendation system and the user satisfaction.

Overall, user satisfaction is positive but constrained by the limited coverage. The current recommendations are perceived as useful, indicating that the value of the system depends on the consistent availability of the recommendations. In the ISSM framework, these findings confirm that the limitations identified in system quality, information quality, and service quality directly constrain user satisfaction (DeLone & McLean, 2003).

4.8 Net Benefits: Business Impact of Recommendations

In the ISSM framework, net benefits are the most important measurement of success, as they capture the balance between positive and negative impacts of the information system on the company's stakeholders (DeLone & McLean, 2003, p. 25). However, DeLone and McLean (2003, p. 25) mention that net benefits cannot be analyzed without the other ISSM dimensions, since the business impact of the system depends on multiple different factors, like technical design, information relevance, and organizational support. In this thesis, net benefits are examined by exploring the business value the recommender system currently provides in the case company's B2B webshop, and whether the organization can measure and demonstrate the value.

4.8.1 Perceived Business Value and Unrealized Revenue Potential

The findings show that if product recommendations are available, they contribute to the company's sales operations in concrete ways. The ICT and Development Director described that multiple store locations where customers need to find an exact spare part for a specific product. He explained that:

> *we have heard stories that the customers want to know that I have this product, for example, this industrial vacuum cleaner, and I want to buy the spare part, for example, this dust bag. And that's an example that comes from many locations because it has to be the exact right product and the right model. That helps a lot our sales* (D).

In these situations, the recommendations help customers to complete the purchase independently, without sales personnel's help, or if salespeople are involved in the customer interaction, the information about the spare part is found effectively. This supports both revenue generation and operational efficiency. The marketing manager also confirmed that the recommendations receive positive feedback from both external and internal users when they are available (A). This indicates that even with the current limited recommendation coverage, they deliver recognizable business value.

However, the findings also indicate that limited coverage of recommendations has resulted in lost business value. The Director of Sales stated that "I believe that we have lost sales because they [related and substitute products] were not available in the best possible way" (C). He further described that customers are increasingly searching for cost savings and that recommendations could serve this need by suggesting alternative products: "with these product recommendations we could also offer the customer savings potential on the webshop side by switching, for example, this product to this product and they would save money. I've received this feedback a few times" (C). These findings

suggest that the business value of the recommender system is constrained not by the concept of recommendations or by user acceptance, but by the ability to deliver them consistently in the webshop by the case company. The perceived value is recognized across all departments in the company, yet it remains qualitative instead of quantified, since the organization currently has no way to measure the recommender system's actual contribution to revenue.

4.8.2 Measurement Gap: Unquantified Business Impact

As mentioned in the previous subsection, the recommender system's business value is recognized in the organization, but the value when it comes to added revenue is based on perceptions and qualitative observations. The findings show that there is no way to track whether a purchase was triggered by a product recommendation or by an independent product search in the company's e-commerce store. The ICT and Development Director explained that the company has only recently started to explore this issue. He stated: "the actual data, that's the one thing that we have started to look at pretty recently so we don't have direct data for that at this point" (D). He further explained the root cause of the problem:

> *we can have data from the products that are added into related products, but we don't know what are actually bought as a related products. Those products also sell separately and individually. So we don't know yet what is bought as related products or as cross-sold* (D).

This finding means that for products that have recommendations, the system cannot differentiate if the customer selected the item because of the recommendation or found it independently.

The marketing manager described the same limitation, pointing out that the measurement gap is specific to the recommendation functionality instead of an analytics problem. She mentioned that:

> *at the moment we don't directly know from where the product has been added to the cart from the recommendation spots. We know the other places but not these recommendation spots. They haven't been separately measured yet. That's coming, so in the future we want to know whether it has an impact. For now it's just guessing* (A).

This tells that other webshop interactions are measured, but the recommender system still operates without any performance measurement, leaving its business impact, when it comes to direct revenue, invisible for the organization.

In the ISSM framework, net benefits feed back into use and user satisfaction, strengthening the system's perceived value and supporting its further development (DeLone & McLean, 2003, p. 24). When the net benefits cannot be measured, this feedback loop is weakened, as the organization has some qualitative feedback of net benefits, but lacks quantitative evidence to evaluate how well the system performs.
As a result, the recommender system's business impact remains perceived but undemonstrated, and decisions about the system's development are based on qualitative feedback rather than measured performance data.

4.9 Synthesis: Key Patterns and System-Level Insights

In the previous sections, the recommender system was examined through each ISSM framework dimension individually. This section brings together the key patterns that emerge when the findings are analyzed collectively. The findings show that the recommender system is effective and trusted by both salespeople and customers when recommendations are available. However, the system's ability to deliver recommendations consistently is constrained by limitations across multiple ISSM dimensions. Table 5.

below summarizes the key factors of the case company's current recommender system and their system-level effects.

Table 5. Key factors from the findings of this study

Key Factor	**Where it appears (ISSM Dimensions)**	**System-level effect**
High accuracy and trusted recommendations	Information Quality, System Quality, User Satisfaction	Builds user trust and makes sure recommendations are accepted when available.
Manual, rule-based recommendation logic	System Quality, Service Quality	Limits scalability and prevents the current system from adapting to customer behavior.
Limited recommendation coverage (~60% without recommendations)	System Quality, User Satisfaction	Leads to inconsistent user experience and is the primary driver of dissatisfaction.
Resource constraints in recommendation creation	Service Quality	Restricts the organization's ability to maintain and expand recommendations at scale
Available data not utilized in recommendation logic	Information Quality, System Quality	Transactional and behavioural data exist but are not integrated, limiting system effectiveness
Absence of performance tracking for recommendations	Net Benefits, System Quality	Business impact cannot be measured, weakening evidence-based development

Three cross-dimensional patterns emerge from the findings. The first is the chain from data quality to business impact seen in net benefits. Limitations in information quality, like inconsistent and unstructured product data, prevent the automation of recommender logic. This is the main reason that keeps the system manual and rule-based, which limits the scalability of the system, resulting in a lack of recommendation coverage in the webshop. The limited coverage affects the use and user satisfaction, as customers and internal employees encounter product recommendations inconsistently. However, the user satisfaction shows that the quality of the existing recommendations is perceived positively. As a result, while the quality of encountered recommendations is perceived positively, the recommendation system cannot support cross-selling consistently across the webshop, and its net benefits remain limited.

The second pattern identified is that service quality is a bottleneck that affects multiple ISSM dimensions. The creation and maintenance of product recommendations currently depend on product managers who handle this work with their other responsibilities. With 67,000 new item codes introduced in a year, this becomes a significant constraint. This limits the system quality by restricting how many products receive recommendations, and it limits information quality by reducing the organization's capability to structure and validate product data. The findings show that ownership of the recommender system is clear and that there is intent to improve the system in the organization, but the capacity is insufficient to execute these improvements in practice with the current system.

The third pattern from the findings is related to the measurement gap identified in the Net Benefits analysis. In the ISSM framework, net benefits are expected to feed back to use and user satisfaction to improve the system over time (DeLone & McLean, 2003, p. 24). The findings show that there is no such feedback loop currently at the case company, since the organization does not have tracking in place yet to measure whether purchases are driven by recommendations or by independent product searches. The business value of the recommender system has been recognized qualitatively across stakeholders, but without measurable evidence, the feedback cannot be translated into evidence-based decisions for further system development.

Overall, the findings suggest that the system is not limited by user acceptance or business relevance, but by the combination of manual processes, unstructured data, limited resources, and the absence of performance measurement. The system does deliver clear value when it is implemented. This indicates that improving only one element in isolation is unlikely to lead to significant improvements in cross-selling performance without addressing the system-level constraints. The implications of the findings and the connection to existing literature on recommender systems in B2B e-commerce are presented in the following chapter.

5 Discussion & Implications

This chapter includes the key findings of the study related to the research questions and prior literature, theoretical and managerial implications of the findings, limitations of this study, and suggestions for future research.

5.1 Key Insights from the Findings

This section discusses the key findings of this study in relation to the prior literature on B2B recommender systems. One significant finding from this study is that the effectiveness of the recommender system in B2B e-commerce context at the case company is shaped mainly by organizational and data-related factors instead of the complexity of the recommender algorithm itself. This contrasts with much of the existing literature of B2B recommender systems, which has focused primarily on improving algorithmic performance. Prior studies have demonstrated that hybrid models outperform collaborative filtering baselines in accuracy (Saraei et al., 2025; Shambour & Lu, 2015), however, the findings of this study show that in practice, organizational capacity to maintain and scale the system may be a more significant constraint than algorithmic capability. The cross-dimensional analysis presented in Section 4.9 indicates that the link from inconsistent data to limited scalability to incomplete coverage is a result of both resource limitations and fragmented processes, as well as the technical structure of the system itself.

This observation highlights that recommender system performance is shaped not only by technical design but also by organizational structures, human expertise, and data governance. Findings show that the case company relies on 20 to 30 product managers to manually define product relationships, which creates what Ricci et al. (2011) describe as a knowledge acquisition bottleneck, meaning that the pace of catalogue growth exceeds the organization's capacity to maintain recommendation coverage. Etra Oy added

around 67,000 new items to its webshop in one year, suggesting that this bottleneck is structural rather than temporary.

The findings reveal an important separation between data availability and data usability. The case company has transaction data, browsing behavior, and customer identification data that are not currently utilized in the recommendation logic to help create personalized recommendations. Zhang and Wang (2015) argue that B2B recommender systems benefit from integrating enterprise back-end data beyond transactional histories. However, this study offers an additional insight that is absent from prior literature. The structural quality of the available data, in this case, including supplier-dependent formatting, free-text attribute fields, and inconsistent measurement standards, can prevent effective utilization of the data. This suggests that for B2B organizations considering AI-driven recommendation approaches, data governance and standardization are crucial.

The findings also offer insights into how B2B purchasing behavior shapes the role of recommender systems. The prior literature consistently indicates that hybrid models outperform rule-based approaches in accuracy and coverage (Kashef & Pun, 2022; Boddu-luri et al., 2024). The findings of this study seem to support this, since limited coverage of product recommendations is a problem of the manual system, and hybrid models are designed to address this challenge. However, the B2B context introduces a significant qualification that is largely absent from the B2C-dominated literature. The interviewees emphasized that recommendation accuracy needs to be near perfect at the case company's context, as incorrect suggestions risk damaging customer trust, which can have long-term negative effects. This corresponds with the observations of Heckel et al. (2017) and Zhang and Wang (2015) regarding the unique transparency and accuracy requirements of B2B purchasing.

5.2 Theoretical Implications

This study contributes to the existing literature on B2B e-commerce and recommender systems in multiple ways. This study is among the first to apply the full ISSM framework (DeLone & McLean, 2003) to evaluate a recommender system in a B2B e-commerce context. The ISSM framework describes its six dimensions as interdependent. However, the findings of this study provide a concrete empirical illustration of how interdependence works in practice as a sequential chain. In the case of the company, inconsistent product data constrains recommendation logic, which limits the system's scalability, which then leads to incomplete recommendation coverage, reduced user satisfaction, and limited net benefits. This indicates that limitations at earlier stages of ISSM can create bottlenecks that prevent improvements at later stages. This observation relates to Jeyaraj's (2020) finding that researchers often apply only part of the ISSM framework, and the sequential nature of these interdependencies would likely be missed if only selected dimensions were examined.

Another contribution is regarding the ISSM feedback mechanism. DeLone and McLean (2003) theorize through the ISSM Model that net benefits feed back into use and user satisfaction, creating a reinforcing cycle that supports continued system development. However, the findings of this study show that this feedback loop does not function at the case company in practice. Since the organization currently has no measuring in place to track if purchases are driven by recommendations or by independent product searches, the business value of the recommender system remains based on qualitative perceptions rather than quantitative evidence. Because of this, the case company appears unable to translate the perceived value into evidence-based decisions for further system development. This provides a concrete empirical example of how the ISSM feedback mechanism can break down in real-world implementations, which the theoretical literature discusses in abstract terms, but that has rarely been documented through empirical case evidence.

Finally, the findings of this study contribute to the broader discussion on the transferability of recommender system research from B2C to B2B context. While much of the existing literature emphasizes personalization and exploratory discovery as drivers of recommendation value, the B2B context appears to position accuracy as a prerequisite for all other dimensions of system success. This finding aligns with the observations of Heckel et al. (2017), who state that the correctness and reasoning behind recommendations are more critical in B2B than in consumer-facing settings, because financial stakes and complexity of B2B transactions are high.

5.3 Managerial implications

The findings of this study suggest several implications for the case company's management. One important implication is integrating performance tracking. Currently, the organization cannot determine if purchases are triggered by recommendations or independent searches, and as findings show, tracking is planned but not yet implemented. Establishing click-attribution on the recommendation placements would create a measurable baseline and help restore the ISSM feedback loop discussed above.

Another key suggestion is that product data standardization should be treated as a foundation and needed before transitioning to AI-driven recommendations. The interviewees showed that there are significant inconsistencies in data quality and that the data is coming in inconsistent formats from the suppliers. This is aligned with Saraei et al.'s (2025) findings that data quality is a precondition for hybrid model performance.

In addition, the case company's transition to using an AI-driven recommendation system is recommended to follow a phased approach. First, implementing a hybrid human-AI model, where AI generates recommendations that product managers validate, appears more appropriate than full automation, given the B2B accuracy requirement. This would help with the scalability bottleneck while maintaining the accuracy standards that the

B2B context demands. This is consistent with the literature on hybrid models (Bodduluri et al., 2024) and B2B transparency requirements (Heckel et al., 2017).

5.4 Limitations and suggestions for future research

This study has several limitations that are important to note. First, this research is based on a single case company, which limits the generalizability of the findings. Second, user satisfaction was addressed only through interviews with the company's internal stakeholders, and no interviews were held with the case company's customers. Finally, the researcher's relationship with the company's employees may have affected the research with unintentional biases.

Based on the limitations of this study, there are suggestions for future research. Multi-case studies across the industry would help assess if the identified constraints are company-specific or generalizable. Also, a longitudinal research tracking system performance before and after AI implementation would provide measurable evidence of the actual business impact. Research involving the end customers would give information on whether an internal perspective of recommendation quality matches the user experience. Lastly, a technical pilot study, where a hybrid recommender system is tested with real data, would add technical evidence to complement the organizational findings of this study.

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Appendices

Appendix 1. Interview Guide: E-Commerce and PIM Manager

Intro of the interview

Introduce the study: The purpose of this study is to gain a deeper understanding of how product recommender systems are currently used in a B2B e-commerce context and to identify the challenges and limitations associated with their implementation and use. The study further examines how AI-based product recommendations can influence cross-selling performance. Based on the findings, the study aims to generate insights that can support the development and managerial adoption of more effective recommender systems.

Introduce your organization: I am a student from University of Vaasa and I am doing a thesis work. University of Vaasa is dedicated to provide excellent studies in university.

Introduce yourself: I am Klaus Huovila, a second year Master's Degree student with a major in International Business at University of Vaasa and conducting this study.

Inform interviewee of confidentiality: This interview is fully confidential and your answers and identity will remain anonymous both in the reports published as well as when analyzing the results.

Inform interviewee of right not to answer a question if they do not wish to: You have the right to not to answer any question and withdraw from the interview at any point of time.

Get consent (verbal or written) to participate: Do you consent to participate in the interview? Please, say Yes, or No

Get consent for audio recording: Do you give consent to have the interview audio recorded? Please, say Yes, or No

1. Role & Webshop Context

- Can you describe your role and responsibilities related to the B2B webshop?
- How central is the webshop today in Etra's overall sales and customer interaction model?

2. Recommender System Overview (Descriptive Baseline)

- Can you describe how the current product recommender system is implemented in the webshop at the moment?
    - *(Probe:)* Has the implementation changed recently?
    - *(Probe:)* Who is responsible for maintaining or adjusting it?
- What types of data does the recommender system currently rely on?
    - *(Probe:)* For example, are recommendations mainly based on customers' past purchases or browsing behavior, on product characteristics and compatibility, or on predefined rules and product relationships?
    - *(Probe:)* Are there data sources you expected the system to use but currently does not?
    - *(Probe:)* How confident are you in the quality of the data used?
    - *(Probe:)* Is offline purchasing behavior reflected in any way?
- Where and at which stages of the customer journey are recommendations shown?
    - *(Probe:)* Why were these locations chosen?
    - *(Probe:)* Are some placements more visible than others?
    - *(Probe:)* Have any placements been tested or removed in the past?

3. Customer Use & Visibility of Recommendations (ISSM: Use)

In a context where customers can purchase through multiple channels, how is the webshop typically used in practice?

- *(Probe:)* For example, does the webshop function as an independent sales channel in some cases, or is it more commonly used in other ways, such as browsing, repeat purchasing, or in combination with sales support?
- *(Probe:)* In which situations do customers rely primarily on the webshop?

- *(Probe:)* When do customers prefer human sales support instead?
- *(Probe:)* Does webshop usage differ between new and existing customers?

- Where in the webshop are product recommendations currently shown during the customer journey?
  - *(Probe:)* Do some of those perform better compared to others?
  - *(Probe:)* Are there stages in the webshop journey where recommendations could have a stronger influence than they do now?
  - *(Probe:)* When do customers rely more on the webshop, and when do they prefer sales support?

4. System Quality – Operational Perspective (ISSM: System Quality)

- From a day-to-day operational perspective, how stable and reliable is the recommendation functionality?
  - *(Probe:)* How often do issues occur?
  - *(Probe:)* Are problems usually noticed by customers or internally?
  - *(Probe:)* How quickly are issues typically resolved?
- Are there issues related to consistency, maintenance, or performance that affect how recommendations appear?
  - *(Probe:)* Do recommendations always appear as intended, or are there situations where they fail to load or are not visible to customers?
- Are there product categories or situations where the system functions better or worse?
  - *(Probe:)* Why do you think performance differs across categories?

5. Information Quality – Practical Relevance (ISSM: Information Quality)

- How relevant do you consider the current recommendations for B2B customers?
- Are recommendations sufficiently context-aware (e.g. customer type, use case, purchase history)?
  - *(Probe:)* Which contextual factors matter most for your customers?
  - *(Probe:)* Are these factors currently reflected in the recommendations?

- In which situations do recommendations fail to match customer needs or expectations?
    - *(Probe:)* Are these failures predictable?
- Do the customers get product recommendations based on what they have purchased before, or what similar companies have purchased before?

6. User Satisfaction & Trust Signals (ISSM: User Satisfaction)

- Based on customer feedback, support requests, or internal discussions, how do customers generally react to product recommendations?
    - *(Probe:)* Do customers question or challenge recommendations?
    - *(Probe:)* Do internal teams trust the recommendations?
- Are recommendations ever mentioned positively or negatively by customers?
- Do customers appear confident relying on webshop suggestions, or do they typically seek confirmation elsewhere?

7. Cross-Selling & Business Impact (ISSM: Net Benefits)

- Thinking about how customers place orders in the webshop, in what situations do they tend to add additional or complementary products during the same purchase?
    - *(Probe:)* What typically triggers this, for example, is it a reminder, product compatibility, prior experience, or something else?
- Do recommendations actually help customers add complementary products, or do they fail to do so, and why?
- Where do you see the largest unrealized cross-selling potential?
    - *(Probe:)* Is this related more to products, customers, or processes?
    - *(Probe:)* Is the limitation technical or organizational?
    - *(Probe:)* Has this potential been discussed internally before?

8. Constraints & Missed Opportunities

- What currently limits the effectiveness of the recommender system?

- Are these limitations mainly related to data, system design, organizational factors, or customer behavior?

9. Closing Reflection (Saturation Check)

- Is there anything about the webshop or recommender system that we haven't discussed but that you consider important?

Closing

Collect demographic information: What is your Name, Title at the company.

Thank the respondent: Thank you for participating in the interview and sharing your valuable experiences. Your answers will help understand current limitations and possibilities in product recommender systems in B2B e-commerce context.

Inform them of what will happen after the interview: After the interviews, I will gather the data from all interviews and write analysis based on that in my thesis.

Provide contact information if they need to contact the organisation about the study: Here is my contact information: x0453729@student.uwasa.fi if you need to or want to contact me about anything. Do not hesitate to send me an email if you have any questions or want to follow up.

Appendix 2. Interview Guide: ICT and Development Director

Intro of the interview

Introduce the study: The purpose of this study is to gain a deeper understanding of how product recommender systems are currently used in a B2B e-commerce context and to identify the challenges and limitations associated with their implementation and use. The study further examines how AI-based product recommendations can influence cross-selling performance. Based on the findings, the study aims to generate insights that can support the development and managerial adoption of more effective recommender systems.

Introduce your organization: I am a student from University of Vaasa and I am doing a thesis work. University of Vaasa is dedicated to provide excellent studies in university.

Introduce yourself: I am Klaus Huovila, a second year Master's Degree student with a major in International Business at University of Vaasa and conducting this study.

Inform interviewee of confidentiality: This interview is fully confidential and your answers and identity will remain anonymous both in the reports published as well as when analyzing the results.

Inform interviewee of right not to answer a question if they do not wish to: You have the right to not to answer any question and withdraw from the interview at any point of time.

Get consent (verbal or written) to participate: Do you consent to participate in the interview? Please, say Yes, or No

Get consent for audio recording: Do you give consent to have the interview audio recorded? Please, say Yes, or No

1. Role & Business Context

- Can you describe your role and responsibilities related to Etra's business operations?

- How important is the B2B webshop from a business and strategic perspective today?

2. Strategic Role of the Webshop (ISSM: Use – Strategic Perspective)

- From a business perspective, what role does the webshop play in Etra's overall sales model?
  - *(Probe:)* How does it contribute compared to traditional sales channels?
- How does the webshop complement or differ from other sales channels at a strategic level?
  - *(Probe:)* Are there overlaps or tensions between channels?
  - *(Probe:)* How do customers move between channels from a strategic viewpoint?
  - *(Probe:)* Has the strategic importance of the webshop changed in recent years?

3. Perceived Business Value of Recommendations (ISSM: Net Benefits)

- From a business perspective, what value do product recommendations currently provide, if any?
  - *(Probe:)* Is this value primarily financial, strategic, or experiential?
  - *(Probe:)* How visible is this value in business discussions?
  - *(Probe:)* To what extent is the value of recommendations discussed based on data versus strategic assumptions?
- Do you see webshop-based recommendations as strategically important for increasing cross-selling or customer value?
  - *(Probe:)* Why or why not?
  - *(Probe:)* Are recommendations discussed as a strategic capability?

4. Customer Value & Satisfaction (ISSM: User Satisfaction – Strategic View)

- How important is customer experience and trust in the webshop for Etra's long-term business?

- From a management perspective, do you believe webshop recommendations currently support or hinder customer value creation?
    - *(Probe:)* In what situations do they add value?
    - *(Probe:)* How tolerant are customers of imperfect recommendations?

5. Cross-Selling & Revenue Impact (ISSM: Net Benefits)

- How important is cross-selling for Etra's business performance?
    - *(Probe:)* How is its success currently evaluated?
- To what extent do you see digital channels, such as the webshop, contributing to cross-selling today?
    - *(Probe:)* Are there product categories or customer groups where cross-selling is especially important?

6. Organizational & Strategic Constraints (ISSM: Service Quality / Constraints)

- What do you see as the main organizational or strategic constraints related to developing the webshop and its recommendation capabilities?
    - *(Probe:)* Are these constraints internal or external?
    - *(Probe:)* Which constraints are most difficult to address?
- Are these constraints more related to resources, priorities, processes, or organizational alignment?
- Ownership decision making: "In earlier discussions, it was mentioned that product recommendations are not shown in the shopping cart or checkout page, and that this decision originated from the owners to keep the purchase process simple and without distractions."
    - *(Probe:)* How are such strategic webshop design principles typically formed and decided within the company?
    - *(Probe:)* When balancing simplicity and potential cross-selling opportunities, how are these trade-offs evaluated at ownership or leadership level?

- *(Probe:)* In general, how open is the organization to testing or experimenting with alternative webshop approaches?
- *(Probe:)* How do ownership-level perspectives shape the direction and pace of digital development?

7. Scalability & International Considerations (SRQ4 Support)

- From a management perspective, what considerations arise when developing webshop functionality across different markets?
  - *(Probe:)* How do customer expectations and purchasing behaviors differ across markets?
- Do you see challenges in scaling digital personalization or recommendations internationally?

8. Strategic Opportunities & Direction

- Where do you see the greatest untapped potential in the webshop from a business perspective?
- In an ideal scenario, what role would the webshop play in supporting sales and customer value in the future?

9. Closing Reflection (Saturation Check)

- Is there anything related to the webshop, digital sales, or product recommendations that we haven't discussed but that you consider important from a business perspective?

Closing

Collect demographic information: What is your Name, Title at the company.

Thank the respondent: Thank you for participating in the interview and sharing your valuable experiences. Your answers will help understand current limitations and possibilities in product recommender systems in B2B e-commerce context.

Inform them of what will happen after the interview: After the interviews, I will gather the data from all interviews and write analysis based on that in my thesis.

Provide contact information if they need to contact the organisation about the study: Here is my contact information: x0453729@student.uwasa.fi if you need to or want to contact me about anything. Do not hesitate to send me an email if you have any questions or want to follow up.

Appendix 3. Interview Guide: Data Specialist

Intro of the interview

Introduce the study: The purpose of this study is to gain a deeper understanding of how product recommender systems are currently used in a B2B e-commerce context and to identify the challenges and limitations associated with their implementation and use. The study further examines how AI-based product recommendations can influence cross-selling performance. Based on the findings, the study aims to generate insights that can support the development and managerial adoption of more effective recommender systems.

Introduce your organization: I am a student from University of Vaasa and I am doing a thesis work. University of Vaasa is dedicated to provide excellent studies in university.

Introduce yourself: I am Klaus Huovila, a second year Master's Degree student with a major in International Business at University of Vaasa and conducting this study.

Inform interviewee of confidentiality: This interview is fully confidential and your answers and identity will remain anonymous both in the reports published as well as when analyzing the results.

Inform interviewee of right not to answer a question if they do not wish to: You have the right to not to answer any question and withdraw from the interview at any point of time.

Get consent (verbal or written) to participate: Do you consent to participate in the interview? Please, say Yes, or No

Get consent for audio recording: Do you give consent to have the interview audio recorded? Please, say Yes, or No

1. Role & Context

- Can you describe your role and responsibilities related to data and analytics?
- How is your work connected to the B2B webshop or digital systems?

2. Data Landscape Relevant to Product Recommendations (ISSM: Information Quality)

- What types of data related to customers, products, and transactions exist at Etra today?
    - *(Probe:)* Are there data types you wish were available but currently are not?
    - *(Probe:)* How has the availability of this data changed over time?
- Are these data sources centralized or spread across different systems?
    - *(Probe:)* Does system fragmentation create challenges in practice?

3. Data Limitations for Product Recommender Systems (ISSM: Information Quality)

- From an organizational data perspective, what data limitations does Etra currently have regarding data relevant to product recommender systems?
    - *(Probe:)* Can you give an example of a limitation that directly affects recommendations?
    - *(Probe:)* Which limitations are the most critical from your perspective?
    - *(Probe:)* Are these limitations technical, organizational, or both?

4. Data Quality (ISSM: Information Quality)

- Are there known challenges related to data accuracy, completeness, or consistency?
- Are some data sources considered more reliable than others?
    - *(Probe:)* How do these quality issues affect analytics or decision-making?
    - *(Probe:)* Are there processes in place to validate or clean the data?
    - *(Probe:)* Have data quality issues caused problems in the past?
- Based on the data available, can products be categorized, and are customers divided into segments in the dataset?
- Is historical purchasing data available?

- Is data available on products that are typically purchased together, both online and offline?
- Are products categorized in a way that supports grouping or similarity analysis?
- Are customers segmented or segmentable in the data?
    - *(Probe:)* How confident are you in the accuracy of these categorizations?
    - *(Probe:)* Are these segmentations actively used, or mainly stored?
    - *(Probe:)* What limitations exist when trying to analyze product combinations?

5. Data Utilization & Gaps (ISSM: Information Quality / System Quality)

- Are there data sources that exist but are currently underutilized or not used at all in product recommender system?
    - *(Probe:)* Is this due to technical limitations, lack of ownership, or resource constraints?
    - *(Probe:)* Have there been attempts to use these data before?
- What prevents these data sources from being used more effectively?
    - *(Probe:)* Which barriers are easiest to solve, and which are the hardest?
    - *(Probe:)* Are these issues more related to systems, processes, regulation, or something else?

6. Data Readiness for AI-Based Personalization (ISSM: Information Quality)

- If the goal were to make product recommendations more context-aware (for example by customer type, purchase history, or product usage), what data-related constraints would limit this?
    - *(Probe:)* Can you give a concrete example of such a constraint?
    - *(Probe:)* How significant is this limitation in practice?
    - *(Probe:)* Is this something that could realistically be improved in the short term?
- From a data perspective, what improvements would most increase the ability to create more relevant and accurate product recommendations?

- *(Probe:)* Would you prioritize improving data quality, availability, or structure?
- *(Probe:)* Which improvements would have the highest impact with the least effort?
- *(Probe:)* How do these improvements align with current organizational priorities?

7. Product Relationship Governance

- In a previous interview, it was mentioned that product recommendations in the webshop are at least partly based on predefined relationships between products. For example, suppliers or internal product managers may define which products are compatible or relevant to recommend together. How are these product relationships technically stored and implemented in the system?
  - *(Probe:)* Is there a standardized process or governance model for defining and maintaining these relationships?
  - *(Probe:)* Or does this depend more on individual product managers or suppliers?

8. Data Infrastructure & Real-Time Capabilities

- Regarding the sales and page view data I received earlier — is this data generated and stored in real time within Etra's systems?
  - *(Probe:)* Or is it processed and updated in batches, for example daily or weekly?
  - *(Probe:)* From a system perspective, would it be technically feasible to use this data for real-time or near-real-time product recommendations?
- Are sales data and behavioral data, such as page views, linked consistently at the customer level across systems?

Closing

Collect demographic information: What is your Name, Title at the company.

Thank the respondent: Thank you for participating in the interview and sharing your valuable experiences. Your answers will help understand current limitations and possibilities in product recommender systems in B2B e-commerce context.

Inform them of what will happen after the interview: After the interviews, I will gather the data from all interviews and write analysis based on that in my thesis.

Provide contact information if they need to contact the organisation about the study: Here is my contact information: x0453729@student.uwasa.fi if you need to or want to contact me about anything. Do not hesitate to send me an email if you have any questions or want to follow up.

Appendix 4. Interview Guide: Director of Sales

Haastattelun aloitus

Tutkimuksen esittely: Tämän tutkimuksen tavoitteena on saada syvällisempi ymmärrys siitä, miten tuotesuositusjärjestelmiä hyödynnetään tällä hetkellä B2B-verkkokaupassa sekä tunnistaa niiden käyttöönottoon ja käyttöön liittyviä haasteita ja rajoitteita. Tutkimuksessa tarkastellaan, miten tekoälypohjaiset tuotesuositukset voivat vaikuttaa ristiinmyynnin “cross-selling” tehokkuuteen. Tulosten pohjalta pyritään tuottamaan näkemyksiä, jotka tukevat tehokkaampien suositusjärjestelmien kehittämistä ja käyttöönottoa organisaatioissa.

Tutkijan esittely: Olen Klaus Huovila, toisen vuoden kansainvälisen liiketoiminnan -maisteriopiskelija Vaasan yliopistosta, ja teen tätä tutkimusta osana pro gradu -tutkielmaani.

Luottamuksellisuus: Haastattelu on täysin luottamuksellinen, ja vastauksesi sekä henkilöllisyytesi pysyvät anonyymeinä sekä raportoinnissa että analyysissä.

Oikeus kieltäytyä: Sinulla on oikeus olla vastaamatta kysymyksiin ja keskeyttää haastattelu milloin tahansa.

Suostumus osallistumiseen: Annatko suostumuksesi osallistua haastatteluun? (Kyllä / Ei)

Suostumus nauhoitukseen: Annatko suostumuksesi haastattelun äänittämiseen? (Kyllä / Ei)

1. Rooli ja myynnin konteksti

- Voitko kuvailla rooliasi ja vastuitasi myynnin parissa Etralla?
- Kuinka usein työskentelet verkkokaupan parissa tai käytät Etran verkkokauppaa?
- Kuinka usein Etran asiakkaat käyttävät verkkokauppaa osana ostoprosessia?

2. Verkkokaupan rooli myyntiprosessissa (ISSM: Käyttö)

- Miten asiakkaat yleensä yhdistävät verkkokaupan ja myynnin tuen ostoprosessissa?
    - *(Lisäkysymys:)* Missä vaiheessa asiakkaat tyypillisesti ottavat yhteyttä myyntiin?
- Missä tilanteissa asiakkaat käyttävät pääasiassa verkkokauppaa, ja milloin he suosivat myyntiä tai muita kanavia?
    - *(Lisäkysymys:)* Riippuuko tämä tilauksen koosta tai tuotetyypistä?
    - *(Lisäkysymys:)* Vaikuttaako ostamisen kiireellisyys tai ajallisuus kanavan valintaan?
    - *(Lisäkysymys:)* Eroaako myyntikanavien käyttö uusien ja pitkäaikaisten asiakkaiden välillä?

3. Verkkokaupan sisäinen käyttö (ISSM: Käyttö)

- Miten myyntitiimit käyttävät verkkokauppaa päivittäisessä työssään?
- Missä tilanteissa myyjät hyödyntävät verkkokauppaa asiakastyössä?
- Kiinnittävätkö myyjät huomiota verkkokaupan tuotesuosituksiin vai luottavatko enemmän omaan asiantuntemukseensa?
- Onko tilanteita, joissa myyjät ohittavat tai muokkaavat verkkokaupan suosituksia?
    - *(Lisäkysymys:)* Tukeeko verkkokauppa myyntityötä vai aiheuttaako se välillä lisätyötä myynnin puolelta?
    - *(Lisäkysymys:)* Ovatko suositukset linjassa myyjien käsitysten kanssa täydentävistä tuotteista?
    - *(Lisäkysymys:)* Luottavatko sisäiset käyttäjät verkkokaupan suosituksiin?

4. Asiakkaiden vuorovaikutus suositusten kanssa (ISSM: Käyttö)

- Mainitsevatko asiakkaat koskaan verkkokaupan tuotesuosituksia myyntikeskusteluissa?
- Näkyykö myyntikeskusteluissa tilanteita, joissa asiakkaat ovat selvästi vaikuttuneita suosituksista tai jättävät ne huomiotta?
    - *(Lisäkysymys:)* Voitko antaa konkreettisen esimerkin?

5. Käyttäjätyytyväisyys ja luottamus (ISSM: User Satisfaction)

- Miten asiakkaat yleisesti kokevat verkkokaupan tuotesuositukset?
    - *(Lisäkysymys:)* Näkevätkö asiakkaat verkkokaupan tuotesuositukset hyödyllisinä vai geneerisinä?
    - *(Lisäkysymys:)* Vaihteleeko tämä verkkokaupan tuotesuosituksien näkeminen hyödyllisinä vai geneerisinä asiakasryhmittäin?
- Luottavatko asiakkaat suosituksiin vai hakevatko he varmistusta myyjiltä?
    - *(Lisäkysymys:)* Mikä aiheuttaa epävarmuutta?
    - *(Lisäkysymys:)* Vaikuttaako tuotteen monimutkaisuus luottamukseen?
- Onko tilanteita, joissa asiakkaat ovat kyseenalaistaneet suosituksia?
- Vaihteleeko tuotetietojen laatu verkkokaupassa tuotekohtaisesti?
- Onko asiakkaat valittaneet puutteellisesta tai epäselvästä tuotetiedosta?
- Miten puutteellinen tieto vaikuttaa ostopäätökseen?
    - *(Lisäkysymys:)* Vaikuttaako epäjohdonmukainen tieto luottamusta suosituksiin Etran tapauksessa?
    - *(Lisäkysymys:)* Joutuvatko myyjät paikkaamaan puutteellista tietoa?
    - *(Lisäkysymys:)* Ovatko tietyt tuoteryhmät ongelmallisempia kuin toiset?

6. Ristiinmyynti käytännössä (ISSM: Net Benefits)

- Missä tilanteissa asiakkaat lisäävät täydentäviä tuotteita tilaukseen?
    - *(Lisäkysymys:)* Onko täydentävien lisätuotteiden lisäys enemmän proaktiivista vai reaktiivista?
    - *(Lisäkysymys:)* Mitkä tuotteet johtavat lisämyyntiin?
- Mikä yleensä käynnistää ristiinmyynnin? (asiakkaan tarve, myyjä, suositus, muu)
- Missä kohtaa myyntiprosessia ristiinmyynti yleensä tapahtuu?
    - *(Lisäkysymys:)* Eroaako ristiinmyynti verkkokaupassa vs. fyysisessä kaupassa tapahtuvassa myynnissä?

7. Suositusten rooli ristiinmyynnissä (ISSM: Net Benefits)

- Perustuen kokemukseesi, auttavatko verkkokaupan tuotesuositukset asiakkaita lisäämään täydentäviä tuotteita ostoksiinsa, vai onko niiden vaikutus vähäinen? Miksi?
    - *(Lisäkysymys:)* Ovatko suositukset hyödyllisempiä tietyille asiakkaille tai tietyille tuotteille?
    - *(Lisäkysymys:)* Missä tilanteissa tuotesuositukset ovat epäonnistuneet?
- Miten Etran verkkokaupassa tehdyt tuotesuositukset vertautuvat myyjävetoiseen lisämyyntiin?
- Missä tilanteissa verkkokaupan tuotesuositukset vähentävät myyjien tarvetta, jos lainkaan?
    - *(Lisäkysymys:)* Onko tämä vähentyminen tarkoituksellista vai sattumanvaraista?
    - *(Lisäkysymys:)* Vaikuttaako verkkokaupan tuotesuositukset tilausten laatuun?
    - *(Lisäkysymys:)* Miten myyntitiimi suhtautuu tähän?

8. Rajoitteet ja haasteet

- Toistuvatko asiakkaiden tarpeet vai vaihtelevatko ne paljon tilauksesta toiseen?
- Mitä pidät verkkokauppapohjaisten tuotesuositusten keskeisimpinä rajoitteina myynnin näkökulmasta?
    - *(Lisäkysymys:)* Mistä nämä myynnin näkökulmasta verkkokauppapohjaisten tuotesuositusten keskeisimmät rajoitteet johtuvat?
    - *(Lisäkysymys:)* Johtuvatko rajoitteet enemmän asiakkaista, tuotteista, luottamuksesta vai muusta?
    - *(Lisäkysymys:)* Kuinka ennustettavia asiakkaiden tarpeet ovat?
    - *(Lisäkysymys:)* Miten nämä rajoitteet vaikuttavat suositusten hyödyllisyyteen?

9. Menetetyt mahdollisuudet

- Missä näet suurimmat ristiinmyynnin menetetyt mahdollisuudet?
- Missä tilanteissa verkkokauppa voisi tukea asiakkaita paremmin?
    - *(Lisäkysymys:)* Missä tilanteissa verkkokauppa voisi tukea Etran myyjiä tai sisäisiä työntekijöitä paremmin?

10. Lopetus

- Onko jotain muuta tärkeää liittyen verkkokauppaan, tuotesuosituksiin tai asiakaskäyttäytymiseen, mitä emme käsitelleet?

Taustatiedot: Nimi, työtitteli Etralla.

Kiitos: Kiitos osallistumisesta ja arvokkaista näkemyksistäsi. Vastauksesi auttavat ymmärtämään B2B-verkkokaupan suositusjärjestelmien nykytilaa ja kehitysmahdollisuuksia.

Jatkotoimenpiteet: Haastattelujen jälkeen aineisto analysoidaan ja tulokset raportoidaan pro gradu -tutkielmassa.

Yhteystiedot: Jos haluat ottaa minuun yhteyttä missä tahansa asiassa tutkimukseen liittyen, voit olla yhteydessä sähköpostitse: x0453729@student.uwasa.fi

Appendix 5. Interview Guide: Marketing Manager

Liite: Haastattelurunko – Markkinointipäällikkö

Haastattelun aloitus

Tutkimuksen esittely: Tämän tutkimuksen tavoitteena on saada syvällisempi ymmärrys siitä, miten tuotesuositusjärjestelmiä hyödynnetään tällä hetkellä B2B-verkkokaupassa sekä tunnistaa niiden käyttöönottoon ja käyttöön liittyviä haasteita ja rajoitteita. Tutkimuksessa tarkastellaan, miten tekoälypohjaiset tuotesuositukset voivat vaikuttaa ristiinmyynnin “cross-selling” tehokkuuteen. Tulosten pohjalta pyritään tuottamaan näkemyksiä, jotka tukevat tehokkaampien suositusjärjestelmien kehittämistä ja käyttöönottoa organisaatioissa.

Organisaation esittely: Olen Vaasan yliopiston opiskelija ja teen pro gradu -tutkielmaa. Vaasan yliopisto tarjoaa korkeatasoista yliopistokoulutusta.

Tutkijan esittely: Olen Klaus Huovila, toisen vuoden kansainvälisen liiketoiminnan -maisteriopiskelija Vaasan yliopistosta, ja teen tätä tutkimusta osana pro gradu -tutkielmaani.

Luottamuksellisuus: Haastattelu on täysin luottamuksellinen, ja vastauksesi sekä henkilöllisyytesi pysyvät anonyymeinä sekä raportoinnissa että analyysissä.

Oikeus kieltäytyä: Sinulla on oikeus olla vastaamatta kysymyksiin ja keskeyttää haastattelu milloin tahansa.

Suostumus osallistumiseen: Annatko suostumuksesi osallistua haastatteluun? (Kyllä / Ei)

Suostumus nauhoitukseen: Annatko suostumuksesi haastattelun äänittämiseen? (Kyllä / Ei)

1. Rooli ja markkinoinnin konteksti

- Voitko kuvailla rooliasi ja vastuitasi verkkokauppaan liittyen?
- Miten markkinointitoiminnot ovat vuorovaikutuksessa verkkokaupan ja digitaalisten myyntikanavien kanssa?

- Kuinka tiiviisti teet yhteistyötä IT:n, tuotehallinnan tai liiketoimintajohdon kanssa verkkokaupan kehittämisessä?

2. Verkkokaupan esitystapa ja suositusten näkyvyys (ISSM: Käyttö)

- Markkinoinnin näkökulmasta, missä ja miten tuotesuositukset esitetään verkkokaupassa?
- Ovatko suositusten sijoittelut linjassa kampanjoiden, tarjousten tai strategisten painopisteiden kanssa?
- Muokataanko tai vaikutetaanko suosituksiin koskaan markkinointitoimenpiteillä?
    - *(Lisäkysymys:)* Oletko kokeillut erilaisia sijoitteluja tai formaatteja suosituksille?

3. Asiakaskokemus ja koettu arvo (ISSM: User Satisfaction)

- Markkinoinnin näkökulmasta, miten tuotesuositukset vaikuttavat asiakaskokemukseen verkkokaupassa?
- Tukevatko suositukset kampanjaviestiä ja brandin positiointia, vai häiritsevätkö ne niitä mahdollisesti?
- Oletko havainnut positiivisia tai negatiivisia asiakasreaktioita verkkokaupan tuotesuosituksiin liittyen?
    - *(Lisäkysymys:)* Uskotko asiakkaiden kokevan suositukset hyödyllisenä ohjauksena vai kaupallisena tyrkyttämisenä?

4. Konversio ja liiketoimintavaikutus (ISSM: Net Benefits)

- Näetkö tuotesuositusten vaikuttavan konversioasteisiin, keskiostokseen tai kampanjoiden suorituskykyyn?
- Seurataanko suosituksia markkinointianalytiikassa tai suorituskykymittareissa?
- Missä määrin suositukset otetaan huomioon digitaalisen markkinoinnin suorituskykyä arvioitaessa?
    - *(Lisäkysymys:)* Onko tuoteryhmiä tai kampanjoita, joissa suositukset vaikuttavat erityisen vaikuttavilta?

5. Organisaation linjaus ja rajoitteet (ISSM: Service Quality – organisaation näkökulma)

- Kuinka hyvin markkinointi, IT ja liiketoimintajohto ovat linjassa verkkokaupan suositustoiminnallisuuden kehittämisessä?
- Onko organisaatiossa rajoitteita, jotka rajoittavat suositusten käyttöä tai optimointia?
- Liittyvätkö nämä rajoitteet pääasiassa prioriteetteihin, resursseihin, järjestelmärajoituksiin vai koordinaatiohaasteisiin?

6. Strategiset mahdollisuudet ja tulevaisuuden suunta

- Markkinoinnin näkökulmasta, missä näet suurimman hyödyntämättömän potentiaalin verkkokaupan personoinnissa tai suosituksissa?
- Jos personointia parannettaisiin merkittävästi, miten se vaikuttaisi kampanjastrategiaan tai asiakaskohdennukseen?
- Ihanteellisessa tilanteessa, mikä rooli suosituksilla olisi asiakassitoutumisen ja arvonluonnin tukemisessa?

7. Lopetus

- Onko jotain muuta tärkeää liittyen verkkokaupan personointiin, asiakaskäyttäytymiseen tai digitaaliseen markkinointiin, mitä emme käsitelleet?

Taustatiedot: Nimi, työtitteli Etralla.

Kiitos: Kiitos osallistumisesta ja arvokkaista näkemyksistäsi. Vastauksesi auttavat ymmärtämään B2B-verkkokaupan suositusjärjestelmien nykytilaa ja kehitysmahdollisuuksia.

Jatkotoimenpiteet: Haastattelujen jälkeen aineisto analysoidaan ja tulokset raportoidaan pro gradu -tutkielmassa.

Yhteystiedot: Jos haluat ottaa minuun yhteyttä missä tahansa asiassa tutkimukseen liittyen, voit olla yhteydessä sähköpostitse: x0453729@student.uwasa.fi

Appendix 6. Interview Guide: Purchasing Director

Intro of the interview

Introduce the study: The purpose of this study is to gain a deeper understanding of how product recommender systems are currently used in a B2B e-commerce context and to identify the challenges and limitations associated with their implementation and use. The study further examines how AI-based product recommendations can influence cross-selling performance. Based on the findings, the study aims to generate insights that can support the development and managerial adoption of more effective recommender systems.

Introduce your organization: I am a student from University of Vaasa and I am doing a thesis work. University of Vaasa is dedicated to provide excellent studies in university.

Introduce yourself: I am Klaus Huovila, a second year Master's Degree student with a major in International Business at University of Vaasa and conducting this study for my thesis work.

Inform interviewee of confidentiality: This interview is fully confidential and your answers and identity will remain anonymous both in the reports published as well as when analyzing the results.

Inform interviewee of right not to answer a question if they do not wish to: You have the right to not to answer any question and withdraw from the interview at any point of time.

Get consent (verbal or written) to participate: Do you consent to participate in the interview? Please, say Yes, or No

Get consent for audio recording: Do you give consent to have the interview audio recorded? Please, say Yes, or No

1. Role & Context

- Can you describe your role and main responsibilities at Etra?

- How does your role relate to product assortment, product information, and webshop development?

2. Webshop Assortment & Supplier Dependency (ISSM: Information Quality / Service Quality – Structural Context)

- From a supplier perspective, is the webshop assortment mainly concentrated around a few key suppliers, or spread across many?
- Are some suppliers strategically more central to the webshop assortment than others? Why?
- What determines whether a product is included in the webshop assortment?
    - *(Probe:)* Does supplier data quality / structuredness influence webshop inclusion?
    - *(Probe:)* Do factors like demand, margin, logistics, or contractual terms influence webshop inclusion?

3. Product Information Collection Process (ISSM: Information Quality – Process Perspective)

- How is product information currently collected before being published in Etra's webshop?
- Do suppliers provide structured product data, or is information enriched internally?
- Is there a standardized template or minimum data requirement for product information?
- Who validates or approves product information before publication?
    - *(Probe:)* Are there formal quality checks?
    - *(Probe:)* Is completeness monitored systematically?
    - *(Probe:)* Are requirements different across categories?

4. Product Information Quality & Variability (ISSM: Information Quality – Structural Perspective)

- Does the quality or completeness of product information vary between suppliers or product categories?
    - *(Probe:)* What are the main causes of this variability?
- Are there specific categories where product information is consistently strong or weak?
- From your perspective, how does variability in product information affect webshop usability and customer decision-making?
    - *(Probe:)* Is technical complexity a driver?
    - *(Probe:)* Are some suppliers consistently better at providing usable data?

5. Product Taxonomy & Attribute Structuring (ISSM: Information Quality – Data Structuring)

- How is product categorization structured in the webshop? Is there a standardized taxonomy across categories?
- Are product attributes (e.g., dimensions, compatibility, standards, use cases) structured consistently or mainly in free text?
- To what extent are product attributes comparable across similar products?
    - *(Probe:)* Do you have attribute standards per category?
    - *(Probe:)* Do category-specific differences hinder standardization?

6. Product Relations & Complementarity Logic

- How are product relations currently defined in the webshop (e.g., complementary products, accessories, substitutes)?
- Are these relationships manually created, supplier-defined, or system-generated?
- Is there a standardized process for defining which products belong together?
- Who is responsible for maintaining and updating product relations?
    - *(Probe:)* Are relations mainly within a category, or also across categories?
    - *(Probe:)* Are relations reviewed periodically?
    - *(Probe:)* Are product managers / category managers involved?
    - *(Probe:)* Are there cases where relation logic is missing or inconsistent?

7. Governance, Ownership & Review Processes (ISSM: Service Quality – Organizational Process)

- Is there a defined process for reviewing and updating product information and product relations?
- How frequently are product data and relations audited or updated?
- Where do you see the biggest bottlenecks in maintaining product data quality or relations?
- Is ownership clear, or fragmented across multiple people, suppliers, or systems?

8. Standardization & Future Readiness (SRQ1 & SRQ2 Support)

- In your view, could product information and product relations be structured in a more standardized way?
- What would be required to achieve greater consistency across categories and suppliers?
- What are the biggest barriers: e.g. resources, systems, supplier limitations, or internal priorities?

9. Structural Impact on Recommendations & Cross-Selling Potential

- From your perspective, how does current product data quality influence the relevance of webshop recommendations?
- Are there situations where recommendations fail due to incomplete or inconsistent product information or missing relations?

10. Closing Reflection (Saturation Check)

- Is there anything related to product information, product relations, or webshop assortment decisions that we haven't discussed but that you consider important?

Closing

Collect demographic information: What is your Name, Title at the company.

Thank the respondent: Thank you for participating in the interview and sharing your valuable experiences. Your answers will help understand current limitations and possibilities in product recommender systems in B2B e-commerce context.

Inform them of what will happen after the interview: After the interviews, I will gather the data from all interviews and write analysis based on that in my thesis.