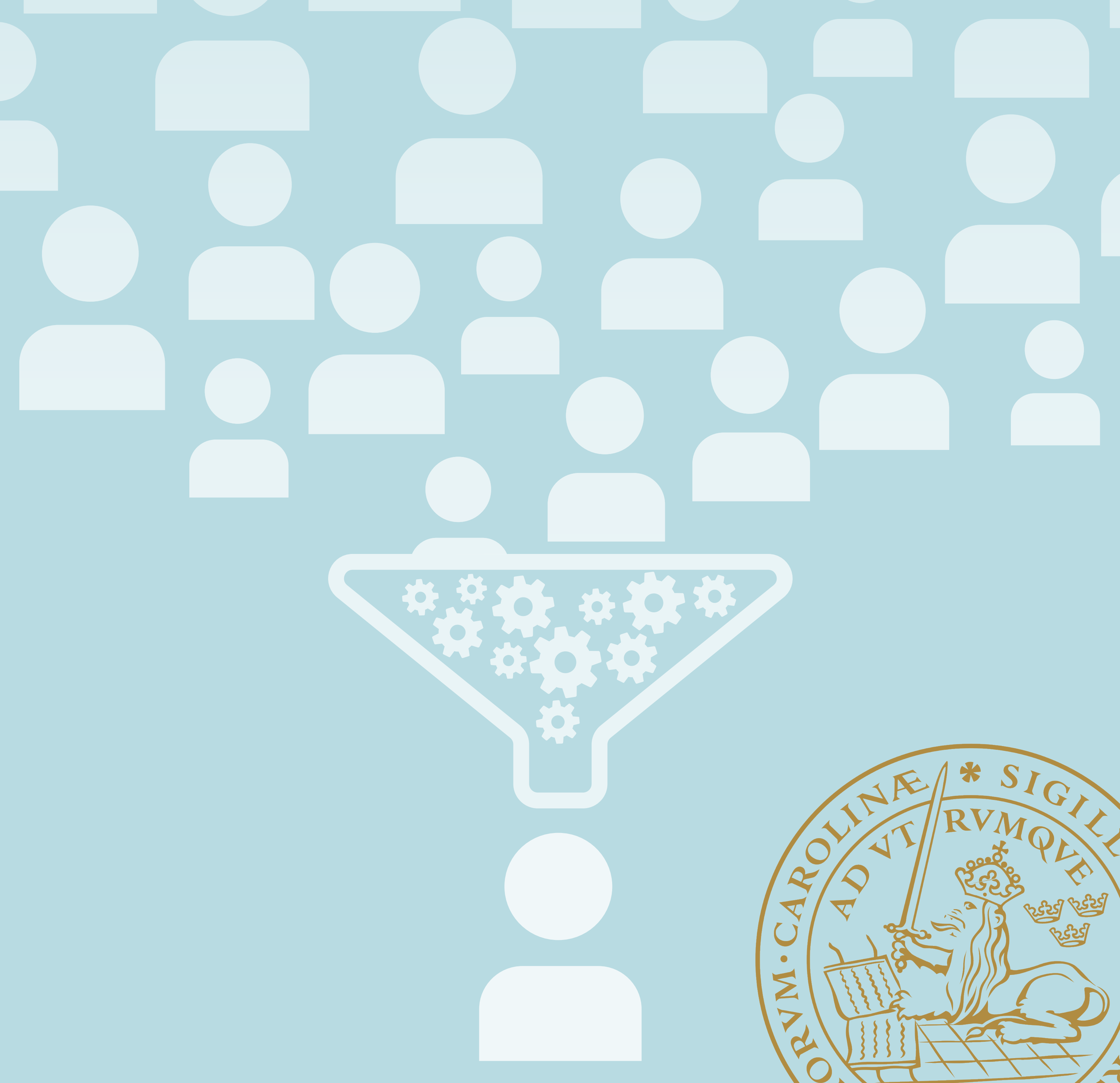
READY OR NOT:

Exploring Machine Learning Readiness in the Supplier Selection Process

Afra Mukhtar & Nazish Rashid

MSc. Service Management | Supply Chain Management | Lund University 2021



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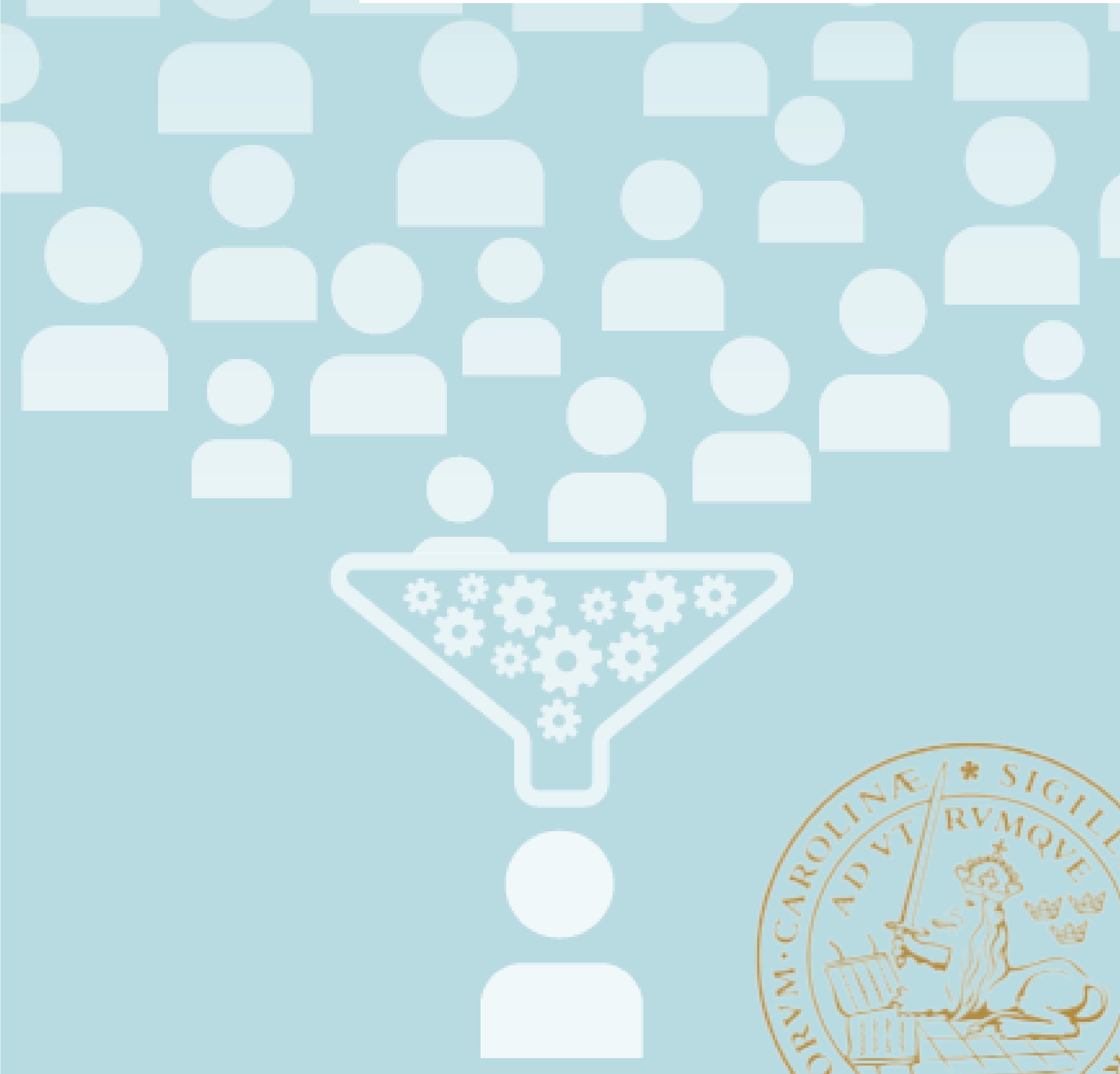

Ready or Not: Exploring Machine Learning Readiness in the Supplier Selection Process

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Abstract

Title Ready or Not: Exploring Machine Learning Readiness in the Supplier Selection Process

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Supervisor Yulia Vakulenko

Purpose The aim of this research paper is to gain a better understanding of machine learning readiness in the supplier selection process. The study aims to analyse the readiness factors that constitute this and barriers that may hinder this process for companies.

Methodology This study made use of a qualitative research approach, which includes a single case study. The case study covers a company interview and a content analysis of company documents.

Findings The findings reveal that academia relates readiness factors to measure readiness in terms of adopting machine learning in the supplier selection process to the industry. However, this study is able to identify several other factors related to three contexts at an organisational level. Furthermore, the findings also validate the barriers found in academia, as well as recognise that additional barriers might hinder machine learning readiness in the supplier selection process.

Value The purpose of this research paper was to connect academia with industry practises, as well as to identify the perception of readiness regarding machine learning technology in the supplier selection process to highlight the gaps within this field of study.

Research Implications This study attempts to enhance insights on the current literature regarding readiness factors and potential barriers for machine learning in the supplier selection process by adding new readiness factors in the existing TOE framework. In addition to that, the authors introduced a new aspect to the framework in the form of barriers that should be taken into account.

Practical Implications The research paper aims to provide valuable insights for procurement professionals in the retail industry to improve their understanding of how a company is able to facilitate machine learning readiness in the supplier selection process.

Key Words Supplier selection process, supplier selection factors, artificial intelligence, machine learning, machine learning readiness, machine learning adoption, TOE framework, TOE

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Helsingborg, May 2021

Afra Mukhtar and Nazish Rashid

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List of Abbreviations

Abbreviations	Explanation
AI	Artificial Intelligence
ANN	Artificial Neural Network
DL	Deep learning
GDPR	General Data Protection Regulation
IS	Information System
IT	Information Technology
MADM	Multi Attribution Decision-Making Methods
MCDM	Multi-Criteria Decision-Making Methods
ML	Machine Learning
NLP	Natural language Processing
RFQ	Request for Quotation
SCM	Supply Chain Management
SSP	Supplier Selection Process
TOE	Technology-Organisation-Environment

Chapter 1. Introduction

This first chapter of the research paper will provide an overview of the background of the overall chosen topic. This is based on the funnel approach, which means that the topic will be narrowed down from general to a specific topic. Section 1.1 will start with the research background. The aim is to provide the reader with a general view of the topic. Then, section 1.2 will be more focused and will present the problem area to explore machine learning readiness in the supplier selection process (SSP). This will be followed by the purpose of the thesis and research questions in section 1.3, and the scope and delimitations of the study in section 1.4. Lastly, an overview of the thesis structure will be presented in section 1.5.

1.1. Research Background

In a rapidly developing business environment, organisations are considered part of a hybrid supply chain system characterised by disruptive technologies such as big data, blockchain, internet of things (IoT) and artificial intelligence (AI) (Bienhaus & Haddud, 2018). Supply chain has the ability to utilise the opportunity for digital transformation to improve performance. Supply chain management comprises a series of integrated processes which include, raw material procurement, production, inventory management, and distribution of finished goods to the end customer (Cooper, Lambert and Pagh, 1997). The efficiency of the supply chain largely depends upon the proper management of purchasing activities, since a major part of total production cost comes from purchasing and outsourcing cost (Park, Shin, Chang & Park, 2010; Ferreira and Borenstein, 2012). According to Ferreira and Borenstein (2012), purchasing of goods and services make up 50% to 60% of the company's total cost. Cooper et al., (1997) describe that the focus of the procurement process is to manage collaborative relations with strategic suppliers to facilitate a smooth production process.

Forming a supplier selection strategy is a crucial part of purchasing and procurement processes (Park et al., 2010). The supplier selection process is vital for effective management of the purchasing process, thus, it can be stated that the focus of supplier management has exacerbated the strategic importance of the purchasing process and the supplier selection has become a priority (Ferreira and Borenstein, 2012; Fallahpour, Amindoust, Antuchevičienė, & Yazdani, 2017). Suppliers are key enablers when it comes to new product designs, cost reduction, and quality improvement (ibid.) Consequently, selecting pertinent and reliable suppliers is a major challenge for a company if it is done to gain a competitive advantage (Tsai & Lee, 2010; Karsak & Dursun, 2015; Cavalcante, Frazzon, Forcellini & Ivanov, 2019).

The supplier selection is recognised as a complex multi-criteria decision-making (MCDM) process which includes multiple and contrasting criteria (Ferreira & Borenstein 2012; Karsak & Dursun, 2015; Fallahpour et al., 2017; Fallahpour, Kazemi, Molani, Nayeri, & Ehsani, 2018). In the past few years, significant attention has been paid to the supplier selection process by researchers and practitioners (Ferreira & Borenstein 2012; Ghorabaee et al., 2017; Fallahpour et al., 2018). Previously, multiple criteria methods have been used to select suppliers including statistical methodologies, artificial intelligence approach, and hybrid approaches (Ho, Xu & Dey, 2010; Fallahpour et al., 2018).

Departing from the aspects above, today's global market is quite complex, and companies are adopting multiple digital technologies in order to compete effectively. In addition to this, companies often carry out business under uncertainties and fluctuations in demand, and supply (Cavalcante et al., 2019). The advent of new technologies such as machine learning (ML), the internet of things, and big data in combination with the accessibility to an enormous amount of data allows companies to use intelligent decision-making applications to deal with business uncertainties (Cavalcante et al., 2019). According to Bienhaus and Haddud (2018), this rapidly changing business environment allows organisations to build new business models and make digital transformation a priority at a management level for all organisations. Among all technologies, AI and ML are considered at the forefront of technological revolutions and impact every business domain such as finance, supply chain management, customer relations, and so on (GEP, 2018). In one of Roland Berger's surveys, AI is ranked among the top three priorities by 67% of companies (Knapp et al., 2018). AI is affecting all supply chain activities from sourcing to logistics through external and internal data sources (GEP, 2018). In particular, digital data from supplier's and purchasing orders provide new possibilities to improve decision making in the sourcing area (Cavalcante et al., 2019.). ML has emerged as a vital and exceptional approach for processing large amounts of data in this digital age (ibid.).

ML is a key subset of the broader AI term, and has the ability to create algorithms that can learn by experience without being programmed manually (Ni, Xiao &Lim, 2020). ML exhibits the ability to process an enormous amount of data and identify complex patterns to make accurate and reliable decisions and projections (Ni et al., 2020; Agarwal & Jayant, 2019). Likewise, the complexity of the supply chain requires new technology to deal with a dynamic business environment (Wenzel, Smit, & Sardesai, 2019). Subsequently, the role of ML is an important factor in supply chain complex decision making. ML is found to be valuable for the supply chain as it has the ability to cope with uncertainty and information inconsistency around supply chain functions and is able to analyse complex relationships (Ni et al., 2020).

Furthermore, ML can be applied to multiple areas in the supply chain such as procurement, production, financial planning, warehouse efficiency, demand planning, network optimisation, and in specific areas such as the supplier selection process (Wenzel et al., 2019). The use of AI and ML are transforming supply chains from traditional to more intelligent, flexible and learning structures that ensure continuous improvement (Jacobs, 2020). It is anticipated that in the coming years, the usage of machine automation will likely grow in supply chains (ibid.). However, it is essential that the organisations evaluate their digital readiness status before making any investments in the innovative technology (Jacobs, 2020).

1.2 Problem Area

As explained in the previous section, AI and ML are changing the business landscape by producing new business opportunities as well as increasing the value and competitiveness for the supply chains. Enormous amounts of data provide the possibility to learn from algorithms, use-cases, and offer efficient solutions that enable ML adoption in the organisations. The field of ML has become a focus of interest for research by scholars and researchers. Previous studies on the adoption of innovation discusses the low rate of ML technology adoption and implementation as well as organisations' readiness to adopt innovative technologies like ML in order to get desired benefits (Tran, Huang, Liu, & Ekram, 2011). The existing literature also points out the fact that at organisational level the research in the machine learning field is constantly increasing, still the knowledge on the topic is deemed limited (Reim, Åström, and Eriksson, 2020). Due to this limited theoretical knowledge, organisations face difficulties in adopting ML in their processes which often leads to undesirable outcomes (Reim et al., 2020).

Jöhnk, Weißert, & Wyrtki (2021) also point out that according to a report, 80% of organisations had a goal to implement AI in their processes, however, only 8% of these had successfully adopted AI in all business operations while others only applied it in individual pilot projects. Thus, it is imperative for organisations to assess the state of readiness before implementing machine learning applications. Previous studies further state that the adoption of innovative technology is multidimensional, which might be affected by organisational, environmental, contextual, or individual factors (Damanpour and Schneider, 2006). However, the authors only describe the general factors (Damanpour and Schneider, 2006). In addition to this, existing literature on technological innovations identifies certain readiness factors for ML adoption with the help of an organisational framework that explains technology adoption in organisations, namely, TOE (based on technological, organisational, and environmental contexts) (Alsheibani et al. 2018, Pumplun et al. 2019). However, it is unclear what specific set of factors as well as challenges would be linked to an organisation's readiness to adopt machine learning. In order to explore this research gap, the authors of this study aim to conceptualise ML readiness, relevant internal and external ML readiness factors and any probable barrier that can cause hindrance in the readiness for adopting ML in the supplier selection process.

1.3 Purpose of the Thesis and Research Questions

The purpose of this research paper is to gain a greater understanding of readiness for machine learning technology in the supplier selection process. Based on the above stated arguments, this master thesis will attempt to explore how organisations facilitate machine learning readiness in the supplier selection process and will explore which factors are able to contribute to this readiness. In addition to this, the purpose has also been to explore what barriers could possibly hinder a company's readiness for adopting machine learning in the process of selecting suppliers. Furthermore, this study will attempt to share the perspective of retail industry professionals that cope with digital transformation and automation adoption process.

This research paper aims to contribute to the academic research in the area of the supplier selection process and machine learning readiness by addressing the gap in the existing literature. Consequently, this paper will attempt to fill this gap through the findings of this research related to ML readiness in selecting suppliers and attempt to do the same for academia on topics such as ML readiness and the supplier selection process in specific. This literature gap will be addressed by determining which factors appear to be most important in facilitating ML readiness in the supplier selection function as well as by identifying which barriers might impede this readiness for adopting ML. Besides, this research will attempt to present the viewpoint and experiences of professionals from 'Company X' on the company's readiness to adopt ML within the supplier selection process. The study aims to provide valuable insights for procurement professionals in the retail industry to improve their understanding of how a company is able to facilitate machine learning readiness in the supplier selection process and enhance supply chain optimisation.

The core of this research paper is to explore which factors facilitate ML readiness in the supplier selection process, and the fact of the matter is that the general set of factors that can impact the innovative technology readiness at an organisational level has been studied before. Hence, based on the aforementioned insights, the first research question seeks to determine the factors that are able to facilitate readiness for adopting specifically ML technology in the selection of suppliers and also attempt to present these factors in comparison to the factors identified in the previous literature. Thus, the first research question is formulated as follows:

RQ1: What factors enable an organisation to facilitate machine learning readiness in the supplier selection process?

The objective of this first question is to determine the factors that enable a company's readiness for adopting machine learning in the process of selecting suppliers.

The second part of this research paper will focus on any possible barriers that exhibit the potential to become obstacles for the organisation's readiness in adopting machine learning for the supplier selection. This means that the second research question attempts to identify the barriers. The research question that has been formulated for this part of the research is as follows:

RQ2: What barriers hinder an organisation's readiness to adopt machine learning in the supplier selection process?

The objective of this research question is to identify the possible barriers that organisations might encounter in the path of preparing ML technologies for supplier selection function. Thus, this question aims to shed light on the important barriers both in literature as well as through case study research.

1.4 Research Scope and Delimitations

Considering the above stated assertions, the focus of the research study will be on machine learning technology readiness, the supplier selection process, and a company's readiness for machine learning adoption for selecting suppliers in the retail industry. This thesis aims to determine the readiness factors and how these can be used by companies to facilitate machine learning applications for the selection of suppliers. In addition, the potential barriers that can hinder ML readiness in the supplier selection process will also be identified. Moreover, the study chose to only investigate one function of the procurement process and narrowed down the scope of research to explore the supplier selection process. Regarding machine learning technology, research has been performed at a conceptual level rather than focusing on technicalities and data or information processing.

The study is limited geographically to the Swedish retail industry and specifically to a single case study of a leading retail company that is located in Sweden. Although the company has a branch in the Baltic area, this has not been studied for the reason that it is active under a different name. Nevertheless, it is probable that the empirical findings of this research are generalisable for the retail industry regardless of a narrow selection since organisations in the same industry usually operate with the same procedures and guidelines. Furthermore, the research is carried out digitally due to the constraints of the Covid-19 pandemic, meaning that the data collection was done through digital channels only.

1.5 Research Outline

This thesis is structured in 6 chapters and are structured as follows:

- The **introduction in chapter 1** will provide the reader with background information on the topic and mentions the purpose of the study, the research questions, as well as the research scope and delimitations.
- The **literature review in chapter 2** will describe what existing literature has been explored and will present the theoretical framework.
- The **methodology in chapter 3** will include an explanation on how this research paper is conducted and designed, along with a critical evaluation, ethical considerations and research methods limitations in the form of critical reflection of the research methods.
- The **findings in chapter 4** will present the research results.
- The **discussion in chapter 5** will include a discussion on the data that has been analysed in comparison to the literature. In addition to this, the research questions will be answered.
- The **conclusion and recommendation in chapter 6** will cover a concluding summary, a reflection, and recommendations for the future research.

Chapter 2. Literature Review

The purpose of the literature review is to provide the foundation of research on the study subject, and to describe the context of the research process (Björklund & Paulsson, 2014). For this specific literature review, the reader is provided a general understanding of the study subject - the supplier selection process and the level of machine learning readiness within this process. Starting with the relevant context such as supply chain management and procurement (2.1), the supplier selection process (2.2), machine learning (2.3), machine learning in the supplier selection process (2.4), machine learning readiness in the supplier selection process (2.5), and the theoretical framework (2.6) will be discussed to ensure that the reader is able to grasp the logic of the research method and context for this study. Lastly, a summary of the literature review will be presented (2.7). All these steps will provide the reader with the relevant background knowledge to better understand this study.

2.1 Supply Chain Management and Procurement

According to Larson and Rogers (1998), supply chain management (SCM) can be defined as the integration of business processes - from suppliers to end consumers, as the latter are provided value in the form of products, services, and information. Correspondingly, Fredenhall and Hill (2001) define supply chain management as a range of interconnected activities, specifically, from raw materials to the end products. Similarly, Anca (2019) describes supply chain management as the integration of key business practises in order to add value to both end users as well as stakeholders, by moving goods, service, or information from the suppliers to end customers. Moreover, Anca (2019) describes SCM as an infrastructure that is needed to move goods, services, and/or data through.

The term SCM has grown exponentially from the 80s to the late 90s, which is reflected in the number of articles in academia (Larson & Rogers, 1998). In a similar manner, Pounder et al. (2013) state that the term of SCM became more important during the 1980s. According to Heckmann, Shorten, and Engel (2013), this term was first coined in 1982 by Webber and Oliver - two consultants at Booz Allen Hamilton, a management and information technology consulting firm. According to Mikalef, Pateli, Batenburg and Van de Wetering (2013), the significance of SCM is great, as this is reflected in the amount of revenue that companies spend on average, namely, over 70% when it comes to supply chain related activities. This fact has been the catalyst for many researchers in academia to conduct research on information technology in the supply chain management field (Mikalef, Pateli, Batenburg & Van de Wetering, 2013). It was especially during the last decade that electronic procurement (e-procurement) systems have received attention in which research was mainly focussed on added benefits such as lower procurement cost, better quality goods, and stronger supplier relationships (Mikalef, Pateli, Batenburg & Van de Wetering, 2013).

Linking different functions such as supply and demand is what ultimately makes a supply chain more efficient and profitable (Nakano, 2020). However, due to many external factors such as the current pandemic or political tensions resulting in loading or route constraints, many companies and organisations are forced to (re)evaluate their SCM, and with that, their purchasing decisions (Thiruchelvam and Tookey, 2011). Generally, the supply chain structure is designed as follows: supplier, distributor, manufacturer, wholesaler, and retailer before it reaches the end customer. However, in reality, companies have much more complex supply chain structures due to factors such as globalisation, the market, suppliers, and their customers (Fredendall & Hill, 2001). Given this growing significance, purchasing related activities have held a vital and valuable strategic position in the area of SCM (Chen et al., 2004).

Monczka, Handfield, Giunipero, and Patterson (2009) state that procurement is considered an important area as this area is able to reduce cost and improve product quality. The procurement function is crucial for the performance of a company, especially due to its intermediary role between suppliers and internal customers, but also since it is able to add value for end users (Chen, Paulraj & Lado, 2004). Procurement refers to the process in which products are sourced (Nakano, 2020). Monczka et al. (2009) defines the procurement process as “The process used to identify user requirements, evaluate the need effectively and efficiently, identify suppliers, ensure payment occurs promptly, ascertain that the need was effectively met, and drive continuous improvement” (p.38). Monczka et al. (2009) highlighted that the purchasing function has certain goals, namely, to manage the supply base, optimise efficiency of the purchasing process, as well as ensure supply flow. According to Murray (2008), procurement and purchasing are often used interchangeably, however, there are important differences. The author continues by stating that purchasing is a subset of procurement as the latter encompasses the purchasing decision and focuses on long term goals such as aligning with the overall strategy and gaining competitive advantage, whereas the purchasing function is rather focused on short term goals and transaction related activities such as the right quantity, amount, cost, etcetera (Murray, 2008).

According to Monczka et al. (2009) suppliers have now become responsible for managing key business processes. Therefore, it is necessary that the purchasing function aligns with this strategy and allows a continuous flow of goods and services. A comprehensive purchasing process model is proposed by Van Weele (2014), as figure 1 below displays the model, which consists of six steps and includes several activities between the internal customer and the suppliers.

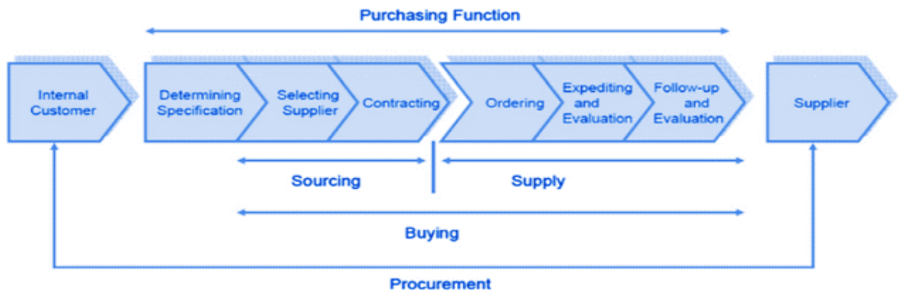


Figure 1. The Purchasing Process Model (Source: Adopted from Van Weele, 2014)

The figure displays the interaction between the internal customer and the supplier, which is referred to as the procurement function (Van Weele, 2014). The purchasing function ranges from the internal customer determining specifications to a follow-up and evaluation of the supplier (Van Weele, 2014). According to Van Weele (2014), sourcing comprises selecting suppliers with the required set of skills and capacity and contracting suppliers in which both parties negotiate on which terms this will be done in order to develop legal agreements and contracts. Both of these processes come after establishing and determining specifications for suppliers (ibid.). After contracting, the supply function begins and consist of the order function and covers the issuing purchase, expediting and evaluation, which refers to closely supervising and controlling to ascertain the supply of purchased goods and services, and lastly, a follow-up and evaluation are carried out to ensure that the predetermined specifications are met by the suppliers (Van Weele, 2014).

2.2 The Supplier Selection Process

Taherdoost and Brard (2019) describe the concept of supplier selection as the process by which firms detect, evaluate, and negotiate with suppliers. In addition, they continue by stating that this process is relatively costly and thus, is an important aspect when it comes to the success of a company (Taherdoost & Brard, 2019). Van Weele (2014) stresses the importance of the supplier selection process as follows: "Supplier selection relates to all activities, which are required to select the best possible supplier and includes determining on the method of subcontracting, preliminary qualification of suppliers and drawing up the 'bidders' list'. Preparation of the request for quotation and analysis of the bids received and selection of the supplier" (p.29). Correspondingly, Sonmez (2006) states that the supplier selection process is an important aspect in procurement. Thiruchelvam and Tookey (2011) describe the supplier selection process as an important component of the purchasing function as this decision becomes a strategic one as this is able to greatly affect the relationship between suppliers and buyers.

According to Tahriri, Osman, Ali and Mohd Yusuff (2008), the supplier selection process is a multi-criterion process that includes qualitative and quantitative criteria. Meaning that a trade-off between these criteria is essential in the supplier selection process (Tahriri, Osman, Ali and Mohd Yusuff, 2008). Similarly, Omurca (2012) states that the supplier selection process is a critical part of the purchasing department, which means that this can lead to complex issues as trade-offs will need to be made. Since consumers demand more quality products at a lower price, timing and after-sales services have increased in importance (Sonmez, 2006). For this reason, companies ought to make a trade-off between criteria such as pricing and quality - to see what is most profitable (Sonmez, 2006). Nevertheless, the supplier selection process is critical for an efficient procurement strategy and overall performance of a supply chain, thus, firms ought to choose reliable suppliers in order to attain supply chain competitiveness (Chen, 2011; Ghorabaeea et al., 2017). More specifically, the supplier selection process is able to assist in improving supply chain functions such as reducing nonessential cost, enhancing operations and managing long-term relations with suppliers and end users (Fallahpour et al., 2017).

Karsak & Dursun (2015) argue that the process of decision making for the supplier evaluation and selection is complex due to two prime issues. The first reason is that it is rather difficult to identify criteria for the supplier assessment and secondly, because it is also a challenge to create a technique or specific strategy for selecting suitable suppliers in the decision-making process (Karsak & Dursun, 2015). Similarly, Taherdoost & Brard, (2019) report that since there is no standard for the supplier selection process, this process is different for every firm depending upon the choice of methods based on their criteria and industry. According to sonmez (2006) the supplier selection process involves two key tasks, which are central to any decision-making problem. Namely, 'evaluation and assessment' and 'accumulation of evaluation and decision making' (Sonmez, 2006). Figure 2 below displays a chart of the steps that need to be taken in order to evaluate and select (new) suppliers: it begins with realising that a (new) supplier is needed and analysing what the current situation is and what is desired (ibid.). This is followed by determining and formulating decision criteria to which decisions will be made in order to have suitable criteria in place that the organisation deems as important and profitable (ibid.).

After this, suppliers are screened during a pre-qualification round which leads to the creation of a list with potential suppliers (ibid.). Lastly, when the final selection of suppliers is chosen, this is followed by regularly assessing them to ensure that the selected suppliers adhere to the predetermined criteria and deliver what is promised (Sonmez, 2006).

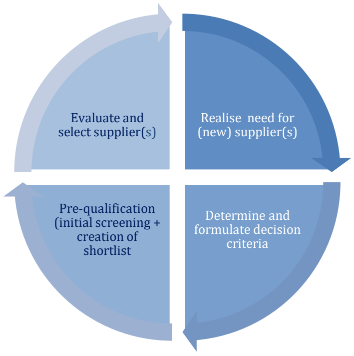


Figure 2. The Supplier Selection Process (Source: Adopted from Sonmez, 2006)

Similar to Sonmez (2006), Van Weele (2014) suggests that the supplier selection process involves four distinct steps, namely, determining the method of subcontracting, followed by a preliminary qualification of suppliers and drawing up a list of bids, then the preparation for the request for quotation (RFQ) and analysis of the bids received and (4) selection of the supplier. Van Weele, (2014) describes that the supplier selection process begins with the actual supply market research, after the buyer has specified the purchasing requirements. As figure 3 below illustrates, the first step of the supplier selection process decides whether to choose the turnkey subcontracting or partial subcontracting method as well as fixed price or a cost-reimbursable agreement. The second step is to determine the prequalification of suppliers on the basis of the purchase order and the supplier must meet these specifications, Moreover, this assessment helps to create a bidders' long list that contains potential suppliers, based on their performance record (ibid.). In this step, the request for information (RFI) will be sent to these suppliers to seek detailed information about their experiences and performance records which often includes a visit from the client and next, most suitable suppliers will be selected, and a shortlist is created with potential suppliers, this list usually contains three to five potential suppliers. In the third step, the requests for quotation (RFQ) are formulated and sent to these qualified suppliers who are then invited to submit a bid that meets the criteria stated in the RFQ (ibid.). The suppliers are able to present these bids so that the buyers can compare the suppliers, this process is termed as tendering. The fourth step involves the evaluation of suppliers' bids where these RFQs are reviewed in detail and finally, suppliers are selected for future negotiations (Van Weele, 2014).

Figure 3. The Supplier Selection Process (Source: Adopted from Van Weele, 2014)

2.2.1 Supplier Selection Criteria

In the past, the traditional approach on the supplier selection was based on the sole criterion of price, however, companies learnt to adopt a multi-criteria approach (Taherdoost & Brard, 2019). This particular approach is divided into two categories, which are multi objective decision-making (MODM) and multi attribute decision making methods (MADM) (Ho, Xu & Dey, 2010; Ghorabaeea et al., 2017). MODM focuses on overall optimisation as it has multiple and often competing goals, whereas MADM is often used to solve a certain (ranking) problem by focusing on one objective using multiple criteria (Kazimieras Zavadskas, Antuchevicience, Kar, 2019). According to de Boer, Labro, and Morlacchi (2001), the latter method refers to a technique in which the decision maker is able to systematically assess the outcomes and alternatives.

Since the 1960s, the supplier selection criteria have been the focus of research for many academics and researchers (Ho et al., 2010; Karsak & Dursun, 2015; Fallahpour et al., 2017; Ghorabaeea et al., 2017). Many scholars have proposed approaches by introducing multiple decision-making criteria (Dickson, 1966; Weber et al., 1991; Ho et al., 2010). The study of Dickson (1966) was the first in this research domain; he listed 23 criteria that purchasing managers in America and Canada used for evaluating supplier performance. The author identifies the most used and vital criteria namely, quality, performance, delivery, cost, warranties and claims policies, production facilities and capacity (Dickson, 1966). In a publication by Weber, Current & Benton (1991), the authors identify three key criteria related to the supplier selection process, namely, price, quality, and delivery after reviewing 74 articles. On the basis of existing literature, Chang, Chang & Wu (2011), presents criteria for ten widely used criteria, namely, quality, service, price flexibility, delivery, lead time, reaction to demand change, production capability, technical capability, and reliability of delivery. They indicate that the stable delivery of goods is considered as a most important criterion for selecting suppliers (Chang, Chang, & Wu, 2011). Similarly, de Boer, Labro, and Morlacchi (2001) mention criteria such as price, quality, process capability, and reliability (e.g., timely delivery) as criteria that are all able to affect the evaluation and selection of suppliers. Likewise, Ho et al. (2010) wrote a literature review on the multicriteria decision-making approaches and point out popular criteria for a reliable supplier selection are price, delivery, quality, management, technology, services, risk, and relationship, manufacturing capabilities, finance, research and development, flexibility, reputation, safety and environment. According to Ho et al. (2010) quality is the most widely used criterion for supplier evaluation. Chen (2011) argues that the supplier selection criteria can be differentiated into two major criteria: competition and organisation. Quality, cost, service, and delivery time criteria come under the competition criteria whereas the organisation criteria contain the criteria of organisational management, technical and production capability and relationships combination (Chen, 2011). Table 1 below contains a summary of the criteria and the descriptions.

Number	Criteria	Description
1.	Cost	- Product price - Logistics cost - Taxes
2.	Quality	- Product quality - Quality improvement
3.	Service	- Customer-based support systems - After sales services - Warranty period - Reaction to demand change
4.	Delivery	- Timely delivery - Flexibility (e.g., payment and shipping) - Reliability of delivery
5.	Supplier profile	- Past performance (reliability) - (Long) Relationships - Finance - Certificates - Reputation
6.	Supplier capacity	- Product range - Production capabilities - Technological capabilities - Process capabilities
7.	Geographical location	- Transportation - Delivery lead time
8.	Environmental aspects	- Environmental awareness - Sustainable production - Management systems - Environmental safety
9.	(External) Risk	- Political - Environmental (i.e., natural disaster) - Financial
10.	Finance	- Financial stability - Refund possibilities
11.	Management	- Organisational management (e.g., staff, culture, communication, continuous process)
12.	Research and development	- Technological innovation

Table 1. Supplier Selection Criteria (Sources: Dickson, 1966; Weber, Current & Benton in 1991; de Boer, Labro, and Morlacchi, 2001; Ho, Xu & Dey, 2010; Chang, Chang & Wu, 2011; Chen, 2011)

2.3 Machine Learning: A Subset of Artificial Intelligence

ML and deep learning (DL) are concepts that belong to AI (Holzinger, Kieseberg, Weippl, & Tjoa, 2018). Thus, AI can be seen as the overarching concept, a subset within AI is ML, and an even smaller subset within ML is DL (ibid.). Figure 4 below displays the structure of AI and its subsets, namely, ML and DL (Holzinger, Kieseberg, Weippl, & Tjoa, 2018).

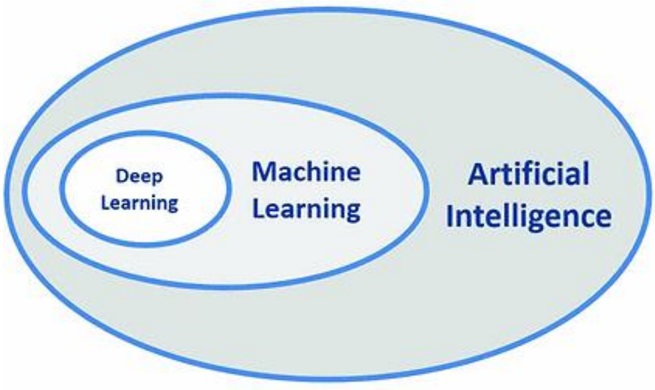


Figure 4. Structure and Subsets of AI. (Source: Adopted from Holzinger, Kieseberg, Weippl, & Tjoa, 2018)

According to Holzinger, Kieseberg, Weippl, and Tjoa (2018), AI dates back to the 1950s. In the first few decades, AI had very high, almost fictional expectations, however, it was only that after the third decade that this started to shift and become more realistic (ibid.). Moreover, AI can be seen as a computer science field that aims to build models that have the capability to learn and make intelligent decisions (Smith & Neupane, 2018). Dash, McMurtrey, Rebman & Kar (2019) define AI as “the ability of a computer to independently solve problems that they have not been explicitly programmed to address” (p.44). In the last few decades, AI has evolved as a robust technology of all times due to the ability of the internet to store and process massive amounts of data (ibid.). In particular, the emergence of AI technologies such as cognitive computing, predictive analytics, machine learning approaches enabled data-driven decision making (ibid.). AI-powered machines exhibit the ability to collect information from specific settings, these machines are capable of learning from the data and these data patterns facilitate actions with substantial accuracy (Dash et al., 2019).

Machine Learning (ML) can be described as a method in which systems are able to learn from data, identify patterns, and conceive a decision with very minimal help of human intervention (Agarwal & Jayant, 2020). This is similar to what Priore, Ponte, Rosillo, and de la Fuente (2019) state, namely, that ML algorithms learn from data, which can be applied to solve a wide range of problems. Likewise, Al-Sahaf, et al. (2019) describe ML as a subset of artificial intelligence and refer to it as learning from experience since ML algorithms work by learning from the data and information. It can be seen as a method where learning can be done in a natural way since ML algorithms learn from data rather than from a fixed framework and the overall performance of an algorithm largely depends on the amount of data (Agarwal & Jayant, 2020). This means that ML algorithms possess capabilities that enhance the accuracy of predictions and help in the decision-making process by learning from data through the recognition of patterns (ibid.). Similarly, Ni, Xiao, and Lim (2020) state that ML algorithms are able to learn from experience and have the ability to handle large data sets and recognise complex relationships and patterns.

Interestingly, the authors Ni, Xiao, and Lim (2020) state that the concept of ML is a term that started to grow towards the end of the 90s. ML is the most eminent and effective approach to AI and the criteria that have led to the successful use of ML technology are namely: accessibility to robust computers, higher capacity, and availability of big data (Smith & Neupane, 2018). However, in a supply chain management context, this remained to a very few articles that were published still (Ni, Xiao, and Lim, 2020). The first peak of ML in the context of supply chain management was in 2008, which was around the financial crisis, the same time when new ways of working, that were less costly, were thought of (ibid.). Not only because it is more cost saving, but also because ML methods have the ability to be more accurate than humans (ibid.). The second peak of ML in supply chain management was around 2016, which was due to the blossoming of AI (Ni, Xiao, and Lim, 2020).

Unsupervised Machine Learning

Agarwal and Jayant (2020) distinguish between two kinds of ML, namely, supervised and unsupervised. The authors continue to describe unsupervised learning as the act of grouping and interpreting data based solely on the input of data, whereas supervised learning refers to the expansion of a predictive framework which is initially based on input and output of data. Additionally, unsupervised learning algorithms function on unlabelled data (ibid.). This means that an algorithm has the capability to discover any pattern and use this particular pattern to draw interesting and/or useful insights from (ibid.). One of the most used methods in unsupervised learning is 'clustering', which refers to an approach where data is analysed and clustered into groups according to the basis of internal patterns of the unlabelled data (Agarwal & Jayant, 2020 ; Al-Sahaf et al., 2019). In unsupervised learning "data is unlabelled, the algorithm finds a hidden pattern and based on these patterns useful insights or inferences are drawn from the data" (Agarwal & Jayant, 2019, p.5). For example, customer segmentation in the supply chain that forms clusters with different groups of customers sharing similar traits or shape associations in the sets of data (Smith & Neupane, 2018; Seyedan & Mafakheri, 2020).

Supervised Machine Learning

Then, there is also supervised learning, which is the most extensively used type and it is "a process in which a computer program is trained by using known example data" (Wenzel et al., 2019, p. 420). In supervised ML, algorithms learn from datasets called training data (i-e. input and output data) which is already known, then the algorithms try to identify core classification patterns from these to categorise new unlabelled datasets (Smith & Neupane, 2018; Seyedan & Mafakheri, 2020). For instance, in the purchasing department, ML techniques can facilitate the decision-making process based on historical data (ibid.). Two main tasks of supervised ML are classification and regression; the objective of both tasks is to develop a model based on the set of known and labelled datasets that can accurately predict the outcome of an unknown case (e.g., trading or the housing market) (Al-Sahaf et al., 2019).

Reinforcement Learning

Interestingly, Smith & Neupane (2018) mention reinforcement learning as a third type of ML algorithm (alongside supervised and unsupervised ML types). In reinforcement learning, at the start of the learning stage, the system is unaware of the best possible outcome, thus it requires it to be learned in a repetitive manner (Wenzel et al., 2019). "Algorithms tend to learn through receiving positive and negative reinforcement from the environment and the system considers complex environmental influences and reacts accordingly" (Smith & Neupane, 2018, p. 108; Wenzel et al., 2019, p. 420). Furthermore, reinforcement learning is commonly used for goal-focused activities such as learning games or skill training (Smith & Neupane, 2018).

Deep Learning

According to Zhang, Tan, Han, & Zhu (2017), DL is an approach that developed from machine learning. They continue by stating that DL actually originates from the artificial neural network (ANN), which is an approach that refers to a network of hidden layers and neural networks are seen as a deep neural network (Zhang, Tan, Han, & Zhu, 2017). Similarly, according to Smith & Neupane, (2018) DL is one form of ANN that employs many hidden layers. It is not known how many layers contribute to deep learning, but it is composed of over a billion layers and besides, DL generally uses supervised and unsupervised machine learning techniques (ibid.). The hidden layers draw complex traits from training datasets and empower DL (Smith & Neupane, 2018). Moreover, neural networks are able to teach themselves to recognise certain patterns from large data sets that they have been fed, without the input from humans (Zhang, Tan, Han, & Zhu, 2017). Additionally, DL starts with raw input of data which is transformed into a representational type of data (Zhang, Tan, Han, & Zhu, 2017).

However, although DL is a promising method within machine learning, Zhang, Tan, Han, & Zhu (2017) mention that this method has certain limitations. One argument is that the large amount of data affects the performance and reliability of DL (Zhang, Tan, Han, & Zhu, 2017). Also, a lack of understanding due to the fact that this method is still a 'black box', which makes interpretation limited (Zhang, Tan, Han, & Zhu, 2017). In addition to that, Agarwal & Jayant, (2020) highlighted that natural language processing (NLP) is also an indispensable part of ML which is pertinent to a technique that transforms data into substantial information that can be made tangible in order to break down big data sets. NLP can be used in both supervised and unsupervised learning (Agarwal & Jayant, 2020). In supervised learning, NLP is able to identify speech, attitudes, and other aspects that are related to text, which means that this method can be articulated as a model that can be used for other texts (Agarwal & Jayant, 2020). When it concerns unsupervised learning, algorithms are used to analyse large data sets and discover meaning and patterns (Agarwal & Jayant, 2020).

2.4 Machine Learning in the Supplier Selection Process

Emerging technologies like ML are able to assist in creating value in the era of digital production as they are able to assist in the process of supplier selection as machines are able to be trained by decision makers to make predictions and help formulate recommendations (Cavalcante et al., 2019). Furthermore, the usage of ML and DL in the supplier selection is able to reduce the amount of time for the decision-maker to analyse and research which supplier would be most reliable and effective, for the reason that ML is able to minimise risk in the supplier selection process (Hiri, En-nadi & Chafi, 2019). Additionally, Wenzel et al. (2019) mention that the timely identification of potential risks is crucial in the supplier selection process. A greater amount of data is able to be analysed by this type of technology, which makes finding important patterns in the search for reliable suppliers more efficient as this can be done with greater precision (Hiri, En-nadi & Chafi, 2019). Thus, ML allows for the decision-maker to make an informed decision based on data from the past (Hiri, En-nadi & Chafi, 2019).

It is evident that ML is the focus of attention given the successful application of machine learning techniques to many decision-making problems (Abdulla, Baryannis & Badi, 2019). Similarly, for the supplier selection, many scholars have suggested machine learning methods as a single approach or as an integrated approach along with other traditional multi-criteria decision-making techniques, such as analytical hierarchy process (AHP; technique to assign weight to various criteria) and data envelopment analysis (DEA; method to improve the efficiency of a decision-making process) (Abdulla, Baryannis & Badi, 2019). Moreover, ML methods have given preference in comparison to MCDM approaches since the usage ML methods have decreased the complexity of the decision-making process and enables the decision-maker to deal with the uncertainty that lies in the decision-making process without any expertise (Guo, Yuan, &Tian, 2009; Fallahpour et al., 2018). These techniques solely require pieces of information about existing scenarios and make a trade off by learning from the historical data (Guo, Yuan, &Tian, 2009; Fallahpour et al., 2018).

As stated earlier, there are two types of ML – supervised and unsupervised ML (Agarwal & Jayant, 2020). Of these two types, supervised learning is the one that is used the most (Wenzel et al., 2019). The main task of this type is to classify and regress, as this helps to achieve the main objective, which is to predict an outcome as accurately as possible. The supplier selection has a very important impact on the control of risks throughout the supply chain and on the increase of its performance (Hiri, En-nadi & Chafi, 2019). Therefore, it is important for decision-makers to understand the long-term impact of their supplier selection strategies and the potential benefits it is able to have on not only procurement, but what this means for the whole company (Hiri, En-nadi & Chafi, 2019).

2.4.1 Machine Learning: Benefits in the Supplier Selection Process

A benefit of using ML techniques in the supplier selection process is that the decision-maker is able to make an informed decision based on large sets of historical data (Hiri, En-nadi & Chafi, 2019). Moreover, applying ML techniques in the supplier selection process can potentially lead to improvement in the selection performance since neural networks select supplier portfolios through historical data, making the selection process smarter and more efficient (Zhang et al., 2016; Fallahpour et al., 2017). Guo et al., (2009) and Fallahpour et al., (2018) pointed out that, unlike traditional methods, which are based on subjective judgment, interpretation of the decision-making process is not needed in ML methods. ML is a robust tool that can support the decision-maker to make a prediction in the supplier selection (Güneri et al., 2011; Fallahpour et al., 2018).

Moreover, in comparison to ML methods, MCDM based models are dependent on subjective judgment and consequently, they are difficult to assess and manage for the decision-maker (Fallahpour et al., 2018). Additionally, the integration of supervised ML algorithms with other MCDM methods can result in improved reliability of suppliers (Cavalcante et al., 2019). Meaning that ML applications enable the decision-maker to deal with decision-making complexity, ambiguity, and uncertainty in a more effective way without taking expert advice and have an edge on other methods (Guo et al., 2009; Fallahpour et al., 2018). More specifically, this process is made more efficient due to the time that is normally spent on analysing and researching information about the supplier and the potential risks is reduced (Hiri, En-nadi & Chafi, 2019). Over time, ML is able to detect patterns, from which decision-makers are able to draw up recommendations (Hiri, En-nadi & Chafi, 2019). Thus, ML is able to enhance efficiency, precision, and eventually save costs (Omurca, 2012).

2.4.2 Machine Learning: Drawbacks in the Supplier Selection Process

Reducing risk is an important part in procurement, thus, it is important to find a balance between opportunities and these potential risks (Omurca, 2012). The main aim of procurement is about building a reliable supplier relationship, which means that transparency and reliability are rather important (Omurca, 2012). This makes the data that is fed to the machine rather important, as it learns from past experiences (Omurca, 2012). However, this also means that there is a great need for a good understanding of the algorithm and strategy of the company in order to know how this impacts the performance of the technology (Omurca, 2012). Similarly, Fallahpour et al., (2017) emphasizes the importance of transparency in algorithms, as these tend to be a 'black box', meaning that it is difficult to present a precise mathematical model for the performance of suppliers on the basis of chosen criteria that are most commonly used in traditional methods (i.e., MCDM approach) for the supplier selection process.

All in all, the review of previous literature pointed out the complexity of the supplier selection process since many authors argued that the decision-making process to evaluate and select suppliers is complex due to issues of selecting appropriate criteria and suitable methods (Karsak & Dursun, 2015; Nakano, 2020). Although machine learning is able to make the supplier selection process more efficient for the decision-maker, it still does not take away the complexity as the ML algorithms remain ambiguous and difficult to understand (Zhang, Tan, Han, & Zhu, 2017 ; Fallahpour, et al., 2017). Nevertheless, it can be concluded that the existing machine learning literature in relation to the supplier selection process, mainly focuses on certain areas within supply chain management whereas others are still under-investigated as this is a relatively new technology (Wenzel et al.,2019). According to Cavalcante et al., (2019), another shortcoming is that although ML applications are growing significantly in supply chain management, current literature fails to provide clear directions on using digital data and how ML techniques can contribute to developing strong supplier portfolios. Likewise, the use of ML methods in the supplier selection process as an individual approach do not result in many research findings (Fallahpour et al., 2017; Abdulla et al., 2019).

2.5 Machine Learning Readiness in the Supplier Selection Process

For companies, artificial intelligence plays an important role to effectively compete in the business market by digitally transforming business functions (Jöhnk, Weißert, & Wyrtki 2021). According to Jöhnk, Weißert, & Wyrtki (2021), intelligent technology such as ML enables organisations to improve work practices, operations, business models as well as provide new business opportunities for gaining a competitive edge. However, not all industries are willing to adopt new technologies and continue to utilize traditional technologies and processes. Procurement and supply chains are also influenced by AI applications which offer efficiency and valuable understanding into complex value chains (Knapp et al., 2018). The authors report that procurement is undergoing a digital transformation and new technologies are reshaping the procurement functions (ibid.). The authors state that the use of artificial intelligence will impact the traditional purchasing process, improve operational transactions, intelligent decision making, and decrease workforce level (Knapp et al., 2018). Thus, the technology changes the procurement enabling automation and efficiency as well as providing an increased understanding of complex supply chain procedures (Knapp et al., 2018).

The incorporation of new technologies such as ML would require new tools and solutions. Tran, Huang, Liu, & Ekram (2011) argue that before investing in technology an organisation ought to fulfill the required readiness level for the technology innovations into business operations in order to ensure successful integration with existing infrastructure. Being ready is the initial stage when planning to implement a new technology, a study report by GEP (2018) addressed the number of conditions before technology implementation, namely, the adoption process needs to be explained to internal stakeholders in order to ensure transparency and trust to make the process more reliable. Secondly, digital transformation influences existing employees and work processes, therefore it is critical to assess the potential impact of transformation on different departments (ibid.). Usage of internal education and on-job training can ensure a comprehensive understanding of the ML applications and alleviate any risk factors. In addition to this, it is essential for companies to identify the right AI suppliers and find the true expertise to implement the ML applications (GEP, 2018).

In one study Tran et al. (2011), describe that readiness of a company for ML adoption might also be affected by managers' perspective about company digital strategy and innovative technology. Jöhnk et al. (2021) argued that it is often easier to use and implement other digital technologies than AI due to its highly complex technical features. Therefore, in order to successfully adopt ML, a comprehensive understanding of related factors, evaluations of organisation's procedures, as well as assessment of the AI adoption goal is required (ibid). Previous literature reflects that the research on the ML adaptation has been performed both on an organisational level as well as the individual level (Damanpour and Schneider 2006; Hameed, Counsell & Swift, 2012). According to Jöhnk et al., (2021) it is essential to understand the relation between the concepts of ML readiness and ML adoption to increase the success level of ML implementation.

According to Pumplun, Tauchtert & Heidt (2019), it has only been recently that research has been done on what factors would constitute 'readiness' factors in the perspective of information systems (IS) according to the technology-organisation-environment (TOE) framework. Baker (2011) describes this as a framework which represents one element of a process within a firm, more specifically, how the firm influences the adoption of innovations such as artificial intelligence. He continues by stating that the framework is an organisation-level theory that describes three aspects in the context of decision regarding the adoption of technological innovation (ibid.). The technological context refers to both (internal and external) equipment and processes, organisational context refers to the way a company is able to organise and facilitate resources (e.g., integration and centralisation of processes), and lastly, the environmental context refers to the size, structure, competitors, and environmental regulations of a company (Baker, 2011).

All of these three contexts have the ability to highlight both the opportunities as well as the barriers for technological innovation (Baker, 2011). Pumplun, Tauchert, and Heidt (2019) describe the TOE framework as a useful tool to start the process of learning more about technological innovations, as it provides a clear overview for a range of technologies. For this reason, it has mainly been utilised for studying more about topics such as big data and cloud computing (Pumplun, Tauchert, & Heidt, 2019). The authors state that this particular framework was extended by utilising the innovation diffusion theory of Rogers from 1995 (Pumplun, Tauchert, & Heidt, 2019). Specifically, factors such as relative advantage, which refers to how a company perceives the innovation compared to what was done prior, and compatibility; the extent to which an innovation in fact matches with the needs of the potential company (Pumplun, Tauchert, & Heidt, 2019). Pumplun, Tauchert, & Heidt (2019) established a few important aspects for each context.

The reviewed literature on ML readiness identified multiple factors that need to be addressed when preparing the organisation to adopt ML in the supplier selection process (Jöhnk et al., 2021). Internal and external business environment and technology characteristics are some of the factors that have an impact on an organisation's readiness to implement ML (Jöhnk et al., 2021). Subsequently, some of these technological, organisational, and environmental factors can be perceived as barriers to readiness of adopting ML (Tran et al., 2011).

2.5.1. Technological Context

Technological readiness reflects the organisation's capability and willingness to adapt to innovative and new technology with regards to the firm's technology infrastructure as well as all external digital technologies (AlSheibani et al., 2018). AlSheibani et al. (2018) pointed out that relative advantage and compatibility to adopt an innovation are important factors to consider when assessing technological readiness and a thorough evaluation is needed to make an adoption decision. According to Tran et al. (2011), in order to implement AI, organisations are required to be motivated to innovate. The authors identify that e-bidding and issues of security are the core factors that can affect a firm's preparedness to adopt AI; these factors can push decision-makers to make implementation decisions.

Similarly, for the technological context, Pumpin, Tauchert, & Heidt (2019) describe that these aspects are relative advantage and compatibility, which they divide into two subsets, namely, business processes and cases. For the business processes, the research reveals that these two aspects must be adapted to the new conditions that the implementation of artificial intelligence brings along (Pumplun, Tauchert, & Heidt, 2019). More specifically, the authors state that with the usage of artificial intelligence, key performance indicators (KPIs) will not be efficient as the technology makes use of attributes (Pumplun, Tauchert, & Heidt, 2019). For example, with artificial intelligence, the company is unable to implement KPIs as the company learns from the data that is created overtime, making particularly data science more important (Pumplun, Tauchert, & Heidt, 2019). Learning to operate in a flexible manner becomes crucial for companies, as data needs to be analysed more often (Pumplun, Tauchert, & Heidt, 2019). Equally as important to the business processes, the second trait that was mentioned often by the participants was a clear and cohesive formulation of a business case, which refers to the fact that artificial intelligence can only be used if the problem is clear (Pumplun, Tauchert, & Heidt, 2019). The authors continue to state the importance of AI as a tool to solve a specific challenge and not as something that stands on its own (Pumplun, Tauchert, & Heidt, 2019).

2.5.2. Organisational Context

Next to factors that are linked to the technology context, there are also factors that can be linked to the overall organisation in regard to the adoption of technological innovation such as AI (Pumplun, Tauchert, & Heidt, 2019). The authors were able to identify two new factors, namely, culture and organisational structure, in addition to the established factors: budget, employees, and information (i.e., data) (Pumplun, Tauchert, & Heidt, 2019). More specifically, the adoption of AI heavily relies on the factor culture, as it often is intertwined with the concept of change management and whether there is a willingness to use (advanced) technology within the company or not (Pumplun, Tauchert, & Heidt, 2019). Not only culture, but also resources is a crucial factor to consider as this has the ability to be a barrier when this is limited, especially when this concerns financial means or a lack of knowledge in employees due to the absence of fitting qualifications and knowledge on programming (Pumplun, Tauchert, & Heidt, 2019). But also, data is an important aspect to consider here, as it should be available and protected in a proper way (Pumplun, Tauchert, & Heidt, 2019). Similarly, AlSheibani, Cheung & Messom (2018) identify the main three factors of organisational readiness namely, top management support, organisation size, and resources. They described that the top management support concerns the involvement and commitment of the firm's top leadership for innovative adoption (AlSheibani et al., 2018). For the organisation size, the authors state that it has a direct impact on the adoption process; moreover, the resources (i.e., financial, human, technology) also plays a crucial role in adopting new technology adoption (AlSheibani et al., 2018).

Reim, Åström, and Eriksson (2020) report that for AI implementations technology, strategic, data, and security are some of core factors to consider and the potential of AI effectiveness depends on the adequate developments of these factors. Strategic factor is identified as a common capability and refers to the digital strategies and development of skills and expertise in digital business while expertise in new digital technologies is considered as technology factors at the company's level (Reim et al., 2020). In addition to this, data deals with data science which includes establishing an appropriate system for the collection of data and also for managing the data (ibid.). The authors deemed security factors as vital in the successful adoption of AI and it mainly concerns cybersecurity skills since organisations need to deal with business data as well as personal data (Reim et al., 2020). Similarly, Jöhnk et al. (2021) identified AI readiness factors at an organisational level in the form of five groups which are deemed to be important for effective adoption of technological innovations. These factors include strategic alignment, culture, resources, knowledge, and data which specify AI focus areas as well as requirements for AI adoption (Jöhnk et al., 2021).

Previous literature reflects that the research on the AI adaptation has been performed both on an organisational level as well as the individual level (Damanpour and Schneider, 2006; Hameed et al., 2012). Depending upon the purpose of implementing AI the organisation must create the required resources, supportive policies, and managerial practices to facilitate the adoption process (Jöhnk et al., 2021). In a similar way, Damanpour and Schneider (2006) categorized factors influencing AI implementation at organisational level into organisation size and complexity, economic health, and external communication are deemed necessary. Being as key elements of organisational design organisation's size and complexity are important indicators of innovations in organisations; in complex organisation information accessibility about digital technologies is high which increases the probability of adopting new technology while organisation size positively impacts the adoption decision (Damanpour and Schneider, 2006). Organisations with strong economic position are more likely to adopt new technology due to the possibility of high investment in innovations (Damanpour and Schneider, 2006). Authors state that one objective of organisations in adopting innovation is to adjust to new environmental trends, thus this information sharing with the environment can facilitate the adoption process by generating new concepts (Damanpour and Schneider, 2006). Correspondingly, Tran et al. (2011) pointed out that the main factors that can contribute to AI implementation include people and process, working environment, organisational structure, culture, and resources.

2.5.3. Environmental aspect

The external environment is a crucial driver for the adoption of innovative technology as this concerns how an organisation assesses environmental factors to implement ML, since business operations are dependent on environmental conditions (AlSheibani et al., 2018). Under this context, aspects such as government regulations, industry requirements and customer readiness are aspects to consider (Pumplun, Tauchert, & Heidt, 2019). For government regulations, the handling of data is of essence for the reason that companies often battle with the usage of personal information to train their intelligent machines, which makes it crucial that this is done in line with the General Data Protection Regulation (GDPR) privacy and security law (Pumplun, Tauchert, & Heidt, 2019). Next to that, the authors state that it is important for each industry to take into account industry requirements as it enables a company to improve their competitive advantage (Pumplun, Tauchert, & Heidt, 2019). The third aspect to consider in this context is consumer readiness, as they are also able to influence this development by demanding customised services, which forces companies to adopt technological innovations to adhere to their customer base (Pumplun, Tauchert, & Heidt, 2019). More specifically, when a company stands for a decision to introduce technological innovations such as machine learning, their customers must be taken into account (Pumplun, Tauchert, & Heidt, 2019). The authors state that competitive pressure and regulatory issues are driving or supporting factors in implementing innovations (AlSheibani et al., 2018). Some of the external factors such as government leadership and support, IT infrastructure support, resources (i.e, human, financial), performance by the government are also the enabler of innovative adoption (Tran et al., 2011).

2.5.4 Barriers to Machine Learning Readiness in the Supplier Selection Process

AI is a valuable tool that can provide solutions to complex problems, but it also implies certain risks and challenges. The implementation of ML in the supplier selection process will present many challenges and barriers such as organisation complexity, management issues, system integration, and IT infrastructure (Tran et al., 2011). The existing literature presented some of the barriers described as follows.

Technology: One of the main barriers to adopt AI in the organisation is the cost of investment for technical solutions, while some of the other challenges are the security of data transactions, system integration, and compatibility issues (Tran et al., 2011). In addition, the lack of knowledge also is an important aspect to consider in this context as a clear and cohesive formulation of the problem is able to truly view AI as a tool to solve it (Pumplun, Tauchert, & Heidt, 2019). Jöhnk et al. (2021) highlighted that the ML-based systems usually have low level of transparency due to the inbuilt complexity of the ML technology which also impedes the adoption of this technology. In ML algorithms process data at different complexity levels (Reim et al., 2020). These highly complex functions undermine traceability, thus generating the issue of the black box (Reim et al., 2020). Consequently, it is very difficult to ensure a high level of transparency and interpretability in an intelligent system and the systems built on such inaccurate or non-transparent models would likely be detrimental to business operations (Reim et al., 2020).

Organisation: Some of the barriers in implementing AI at an organisational level includes complex organisational hierarchical structure, difficulty in motivating employees to adopt new technology, different organisational culture, scarcity of (financial) resources, lack of internal education, unskilled workers, and lack of commitment from top management (Tran et al., 2011 ; Pumplun, Tauchert, & Heidt, 2019). Trust lacking for AI- Trust is an essential element in deciding to implement AI. Trust issues linked to how the management communicates about AI within the organisation as well as about the nature of the technology (Reim et al., 2020). If employees lack clear understanding about the AI it might be difficult to adopt it, therefore, building trust in the firm is vital to successful digital transformation (Reim et al., 2020).

Environment: External factors can act as an obstacle to implementing the AI in procurement such as a lack of a national IT policy or poor IT policy, an effective legal and regulation system, inadequate IT infrastructure, lack of data protection (i.e., not in line with GDPR) and lack of marketplace and supplier's readiness, as well as customer readiness (Tran et al., 2011 ; Pumplun, Tauchert, & Heidt, 2019). In addition to this, data sharing and information exchange are also considered critical in conducting business operations with external trading partners, however, these partners are often hesitant to share data due to the market competition and maintain the competitive advantage (Tran et al., 2011).

2.6 Theoretical framework

Based on existing literature, the factors in the theoretical framework (see figure 5) focus on the level of readiness for adopting machine learning. These factors are technology-related factors, organisation-related factors, and environment-related factors as well as barriers to consider when wanting to adhere to a level of readiness to adopt machine learning applications in the supplier selection process. The theoretical framework can be seen as the foundation for the findings and discussion in this research paper.

The technology-organisation-environment (TOE) framework is one of the theories on technological innovation and technology adoption. The other common theories are the Technology Acceptance Model (Davis, 1986), Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis and Davis, 2003), Diffusion of Innovation (DOI) (Rogers, 2003), and so on. However, the literature indicates that most of the theories or models are unable to provide a comprehensive model of innovative technology adoption (Tran et al., 2011). Although the review of the previous study reveals that the TOE-framework has been broadly explored in the field of new technology adoption (AlSheibani et al., 2018). Tornatzky & Fleischer (1990) have developed the TOE framework which describes that technological context, as well as the organisational and environmental contexts, influence the decision making regarding innovative technology adoption. A comprehensive overview of the readiness factors and the descriptions are shown in table 2 below. The technological context includes internal and external technological practices and designs (Tornatzky & Fleischer, 1990). The organisational context focuses on organisational attributes such as structure, size, and resources that could affect the decision of adoption and implementation of innovation (Tornatzky & Fleischer, 1990). The environmental context defines in terms of firms' stakeholders such as competitors, suppliers, government, and customers and how they might drive the firm's need for innovation and new technology implementation (Tornatzky & Fleischer, 1990).

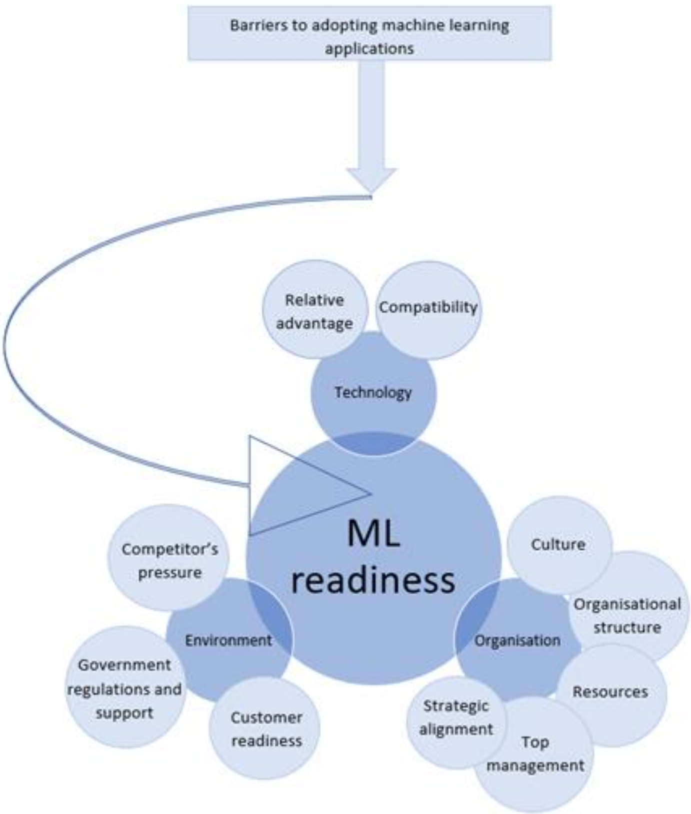


Figure 5. Theoretical Framework (Source: Adopted from Tornatzky & Fleischer, 1990)

The TOE-framework reflects that the appropriate use of external and internal factors can facilitate the organisation's readiness to adopt new technology (Aboelmaged, 2014; AlSheibani et al., 2018). However, Aboelmaged (2014) also argues that the TOE-framework is unable to propose a specific set of factors that influence the technology adoption process. Therefore, for this study, the chosen factors are based mainly on TOE-framework assumptions as well as other related studies and have been used as ML readiness in the supplier selection process with some amendments. For this particular research paper, the factors of the TOE-framework are integrated throughout the study and the research framework enables the authors to focus on the effects of technology, organisation, and environment to explore the level of readiness of machine learning in the supplier selection process. The research framework in figure 5 displays three overall contexts that drive technological innovation, as well as related sub-factors. In addition, the authors added barriers to adopting ML applications in the supplier selection process to highlight the challenges that companies might encounter during this process.

Themes	**Characteristics**
Technological context	
Relative advantage	The extent of expected benefit of implementing innovation at an organisation. When a firm intends to adopt new technology, it is critical to evaluate if the technology is perceived better than the other competing technologies.
Compatibility	The degree to which a new technology exhibits the ability to offer value persistent to the company's existing values as well as address the adopters' requirements. Additionally, the technology implementation requires a stable business position and must align with the organisation's current business process and cases.
Organisational context	
Culture	To a very large extent this factor is linked to the concept of 'change management', thus, whether there is a willingness to adopt and implement technological innovation within company processes.
Organisational structure	A changing organisational structure is inevitable with the adoption of technological innovation. As this may lead to changing roles within the company, this might also have an effect on the complexity of a company structure and may vary depending on the size of the company. It is not clear whether bigger companies have a greater probability of adopting artificial intelligence, however, having greater resources and a bigger customer base provide them with more reason to do so.
(Financial and human) resources	Resources can be divided into financial means (i.e., budget), employees, and data. enable a company to adopt and implement new technological innovations. To which degree an organisation is able to do so is largely dependent on the extent of these resources. Sub-factors that can be included in this main factor are budget, employees, training, and education (i.e., employee focused).
Top management support	The degree to which the top-management can make decisions that support the adoption and implementation of technological innovation within company processes.
Strategic alignment	This factor refers to the compatibility of a company in regard to artificial intelligence innovations. Especially when it comes to readiness, it is important to have a level of awareness in terms of solving a problem or aiming to seize a new opportunity.
Environmental context	
Competitor's pressure	Competitive pressure concerns the risk of losing or failure in maintaining a competitive advantage in the industry. This competition forces firms to speed up the adoption process for new technologies in order to take a competitive edge over rivals.
Government regulations and support	This is an important factor to take into account when making a decision on adopting new technology. Government regulations reflect the support provided by the authorities to motivate organisations to adopt innovative technologies.
Customer readiness	New technology requires customer understanding of technical complexity otherwise it might influence customer readiness. This lack of customer readiness and demand can affect the adoption process.

Table 2. TOE Framework: Readiness Factors Summary (Source: Adopted from Tornatzky & Fleischer, 1990)

2.7 Summary of Literature Review

Summary of Literature Review	
2.1. SCM and Procurement	A background on SCM and procurement is provided.
2.2. The SSP	The literature focuses on presenting existing literature on the supplier selection process, as well as the supplier selection criteria. 2.2.1 Supplier Selection Criteria
2.3. ML: A Subset of AI	The literature presents background information on the structure of AI, ML, and DL, as well as a deeper understanding on specific types of ML.
2.4. ML in the SSP	The concept of machine learning is explained in accordance with artificial intelligence, deep learning, types of machine learning, and algorithms. In addition, the benefits and drawbacks of ML in the SSP are highlighted. 2.4.1. ML: Benefits in the SSP 2.4.2. ML: Drawbacks in the SSP
2.5. ML Readiness in the SSP	The literature presents ML readiness factors in accordance with the TOE framework, which originally consists of three contexts. Namely, technology, organisation, and environment. In addition to these three elements, the authors also take into consideration the barriers that a company might encounter in the same manner, thus, in line with the TOE framework themes. 2.5.1. Technological Context 2.5.2. Organisational Context 2.5.3. Environmental Context 2.5.4. Barriers to ML Readiness in the SSP
2.6. Theoretical Framework	The theoretical framework for this study is explained in accordance with the TOE framework.

Table 3. Summary of Literature Review

Chapter 3. Methodology

This chapter of this study will present a description of the overall research process. It will provide the reader with information regarding the method that was used, as well as a justification for this particular choice. This chapter is divided into seven sections. Section 3.1 will present the research philosophy and the research approach. After this, section 3.2 will present the research design. Then, section 3.3 will provide information on the data analysis process. After this, a critical reflection on the research methods will be described in 3.4. Ethical considerations will follow after reflecting on the methods in 3.5. Section 3.6 will contain a critical reflection on the research methods. Finally, table 6 will present a summary of the methodology in section 3.7.

3.1 Research Philosophy and Approach

3.1.1. Philosophy

Research methodology plays a critical role in the research process since it provides the framework for carrying out research. Therefore, it is crucial to grasp the roots of the methodological approach in order to justify why the chosen research method is appropriate for the research study. Every step of the research process builds on the researcher's viewpoint that reflects the nature of knowledge. The research philosophy is linked to the nature of knowledge and its sources. In order to explain the perspective of this research, the authors established epistemology and ontology schools of thought that support the choice of research method. The selection of a suitable methodology can be rather challenging as this affects the stance one is ought to take. Certainly, the position of the authors is connected to how this research is conducted. Before the stance of the authors is clarified, the concepts of epistemology and ontology will briefly be described.

According to Bryman (2012), ontology is concerned with a particular ontological position that upholds social phenomena and their meanings. For this research process, a constructivist position was able to assist the researchers to better understand social phenomena and that the meaning of this is something that changes continuously (ibid.). Moreover, this considers whether the social reality is constituted by social actors' actions or the existence of social reality does not depend on social actors. (ibid.). This particular ontological approach allowed the researchers to understand that the knowledge that is obtained and analysed throughout the qualitative research are continually being accomplished by social actors (ibid.). The constructivist approach helped the researchers to gather knowledge based on the experiences and opinions of the people working in the same social settings (ibid.). As the research process required a combination of interpretation, analysis, and synthesis, this means that knowledge is something that is constructed rather than invented (Bryman, 2012). As both authors are students from the social scientist faculty, where both have learnt to conduct similar studies in the past few years.

According to Bryman (2012), epistemology can be described as science that is concerned with what should be regarded as admissible knowledge. The author continues by stating that epistemology is concerned with the stance that the researcher takes on and has implications on how research is conducted (ibid.). By choosing an interpretivist approach for this qualitative research paper, the researchers' main objective is to understand how reality is understood, and how this differs from person to person (ibid.). According to Bryman (2012), this means that truth and reality is different for everyone as this is something that is based on social interactions between social actors. Additionally, this means that the authors also bring forth their personal interpretations when analysing data (ibid.).

Additionally, an important part of conducting interviews was for the authors to maintain open-mindedness to the interviewees and their answers as this enables the interviewee to feel more comfortable and relaxed in sharing about their experiences (Flick, 2014). For the present study, the researchers aimed to conduct this research in the most objective way possible, however, it seems that this cannot be done in its entirety due to the fact that part of the research consists of an interview and content analysis based on videos. This means that experiences, views, and beliefs of individuals are shared and accumulated by the authors. Meaning that this also impacts the study.

3.1.2 Research Approach

On the basis of the above stated ontological and epistemological stance, a research approach has been taken which illuminates the methodological path of this research process. For this research, the authors made use of a deductive approach as this was deemed most fitting for this research paper. The authors began with studying what others had done throughout the previous years and read up on previous literature, which allowed them to establish a foundation. This foundation is what is accumulated and formed the base for this paper, namely, the literature review (Bryman, 2012). After reading up on existing theories and previous literature, the authors explored the topics that emerged from these topics further in order to connect theory to practise (ibid.). As Bryman (2012) mentions, inductive and deductive approaches are not strictly linked to qualitative or quantitative research. In fact, both approaches have similar elements, thus, for the authors it was only natural to go back and forth between data and theory to ensure that issues are identified as early as possible, valuable feedback was taken into account throughout the process, and that theory is put into practise (ibid.). This was also the case for this particular research, which is referred to as an iterative process (Bryman, 2012).

By following this process, the researchers had a foundation of knowledge to which they were able to build further upon through the usage of a company interview and content analysis of company documents and videos, to test whether the theory is correct or not (Bryman, 2012). More specifically, the authors went back to the theory after interviewing the automation expert to ensure that the questions were suitable for this research paper, specific enough, and whether a follow up of questions was needed. Additionally, after a substantial amount of data had been collected, patterns were identified. The researchers believe that a deductive approach is the most fitting for conducting this study for the reason that it helps the researchers to build a foundation of knowledge on the methods and practises within the chosen topic. Moreover, existing concepts were theorised, and relevant previous literature was explored, which was later on complimented by the usage of data that emerged from the semi-structured interview, company documents and videos to support the theory (ibid.).

Unlike the inductive approach, which is concerned with generating new theories, a deductive approach uses the theoretical concepts available in the specific field of research and investigates present theories with new aspects and views (May, 2011; Bryman, 2012). Since the literature on existing theories in regard to the applicability of machine learning in the supplier selection process is a relatively new feature, this means that the articles are relatively new. This also indicates that there are research gaps that are also addressed by the authors. Therefore, the first step in the research process was to gather data in order to compare it to current theories and use this as a benchmark for the case study. The data was collected through a company interview as well as a content analysis based on company documents and videos. The researchers jumped back and forth from theory to data and data to theory to outline the gap between what is and what should be.

All in all, by following a deductive approach with an iterative strategy, the authors were able to complete this study under favourable conditions as they were able to learn, go back, and adjust throughout the research process. Researching previous knowledge on the topic of machine learning readiness in the supplier selection process enabled the authors with a vital foundation for this paper in order to write the literature review, which was later complemented by the collected data through the usage of a semi-structured interview, company documents and videos.

3.2 Research Design

The research design provided the structure that guided the research process and also gave the foundation for gathering and analysis of data in order to answer the research question in the best way possible (Bryman, 2012). For this research paper, the data collection phase comprises primary data and secondary data. The primary methods included a qualitative semi-structured interview, a single case study. For secondary data, the authors made use of a literature review and content analysis based on company documents and videos. This thesis is based on a qualitative case study that focuses on the readiness of machine learning in the supplier selection process. According to Ellram (1996) a case study method can be used in business research, especially in purchasing and logistics research. The author argued that while quantitative methods are commonly used in purchasing, logistics, and operations management, qualitative methods are increasingly recognised as an alternative approach (Ellram, 1996). The purpose of performing a qualitative study was to gain insight into whether there is a gap between what exists in academia and what is being used in practice in the retail industry when it comes to the readiness of machine learning in the supplier selection process.

3.2.1. Literature Review

The research of relevant literature had the purpose to specify the research area, to gain a comprehensive understanding of what is currently known about the topic to identify any potential research gap in the literature. The collected literature gave a broad view of the knowledge on the selected topic and provided the frame of reference for the data analysis in the later stage. The literature included in this study was collected from various sources namely, Lund University's official database LUBsearch, Google scholar, and books to provide theoretical reference. In order to establish background knowledge, multiple keywords have been used to explore previous studies.

In the first stage, the keywords supplier selection, supplier selection factors, supplier selection process, and supplier selection methods have been used which resulted in a large number of academic articles. In the second stage, to explore the background of artificial intelligence (AI) and machine learning (ML) alone but also in connection to an organisation's readiness, the authors searched for literature by using the keywords artificial intelligence in supply chain management (SCM), machine learning in SCM, machine learning readiness in procurement, and ML readiness which resulted in a relatively high number of articles. The aim of the third phase was to connect the topics of machine learning and the supplier selection processes together and used keywords of the first stage and second stage together. Namely, supplier selection process and ML, supplier selection and ML, artificial intelligence and supplier selection process, ML readiness and supplier selection process. However, when comparing the amount of hits of all three stages, this last search led to the least hits. Nevertheless, the literature search helped to create a foundation for the research in order to facilitate the interview phase. The articles that were included in the literature review had a timeline of the year 1966 to 2021 and included perspectives on the supplier selection from around the world, however, most of the academic articles were centred around a European and Northern-American perspective. Overall, the literature review provided the authors with background knowledge on the subject area (i.e., core concepts and evolution of these concepts over time).

3.2.2. Single Case Study

The motivation behind choosing the case study as a research method was to draw broader conclusions from real-life contexts. According to Yin (2003), a case study helps to understand complex social phenomena, allow the researcher to present a holistic view, and provide significant insight of individuals, groups, organisations, and related social situations by asking 'how' and 'why' type of questions. Yin (2003) and Ellram (1996) argue that the case study method is a commonly criticised and less understood research method, nonetheless case study methodology is increasingly considered as an alternative approach in business context. In addition, Ellram (1996) claims that the case study method has been less desirable because of misperceptions linked to the method. Some of these misperceptions are that the method is only used for qualitative research, that it is only appropriate for the exploratory stage of the research, that case study methodology design is not rigorous, and lastly, that case study findings are not generalisable (Ellram, 1996). However, Yin (2003) argues that the case study method has been increasingly adopted for organisations' research.

The focus of this case study will be on machine learning readiness in the supplier selection process, and more specifically, whether the case study company is ready for an intelligent solution in the form of machine learning when it comes to this process. Usage of a case study enables the authors to collect data through both a semi-structured interview and content analysis of company documents and videos to make the collection of data more saturated. Case studies make it possible to investigate the events as they happen in the company, it is able to provide the authors with a deeper understanding of reality (Yin, 2003). In fact, this was also the reason that the authors chose to opt for a case study method because it was able to help facilitate more concrete and in-depth examples (Yin, 2003). One of the most important components of a case study is the unit of analysis, also termed as "case", which is related to identifying the case to describe what is being studied (Yin, 2003). Moreover, this can be an individual, event, or entity (ibid.). The selection of a suitable unit of analysis is related to the primary research questions (Yin, 2003). The unit of analysis for this specific research paper is machine learning readiness.

In order to increase the reliability of the case study, a research protocol has been formulated which was based on the protocol criteria described by Yin (2003) namely, a case study overview, field procedures, and case study question (see case study protocol in appendix 3). This protocol serves as a guide for the authors to collect data from the case company (Yin, 2003). In addition to that, the case study method enhances the trustworthiness and credibility of the interview and ultimately, of the research process since the authors used company resources such as articles, reports, and videos (Bryman, 2012).

For this research, the authors made use of both primary and secondary data collection. Through primary data collection, the researchers were able to collect first-hand data from the company that was part of this research paper through the usage of a semi-structured interview. The importance of primary research data is considered to be valuable as the authors were able to generate relevant data. In order to gain a deeper understanding of contemporary challenges and opportunities that are related to the research area, the case study was to be found a suitable method as case studies are known to focus on situations that reflect reality.

3.2.2.1. Introduction to the Case Company: 'Company X'

This section presents the case study of 'Company X', and the supplier selection process at the case company in order to get a comprehensive understanding of the company's readiness to use ML applications for selecting suppliers. In order to conduct this study, the research was performed through an empirical interview and an in-depth content analysis of company documents and videos to explore the internal process of selecting suppliers and to get an understanding of the digital (ML) readiness for the supplier selection process.

Although the case study is centred around 'Company X', the intention is that it is an insightful case study for other companies within the retail industry. The authors of this research study chose to have 'Company X' as a case study for the reason that the company is active in a dynamic and highly competitive industry. The history of 'Company X' can be traced to the early 1900s. Since then, it has evolved and grown significantly. In their annual report of 2020, the retailer stated that they have a market share of approximately 35% and over 1000 stores (Company X, 2021). The case company has various subsidiaries and has a collaborative business model with independent retailers in not only Sweden, but also in the Baltic area (Company X, 2020). Within the company, coordination is encouraged through increased harmonisation in key areas such as sourcing (Company X, 2020). The company has a great focus on digital and technological innovation and aims to establish long-term profitability and sustainable growth in an industry that is rather competitive and big in scale (Company X, 2020).

'Company X' has many international suppliers for the purpose of both sourcing and the production of their products (Company X, 2020). In fact, the majority of their suppliers are located in Europe, however, the company also has suppliers from Asia and Africa. When it comes to sourcing and production, the company strives to work with suppliers that produce under acceptable human rights conditions (Company X, 2021). Moreover, to ensure that these requirements are met, social audits are done, and suppliers are offered training to improve conditions (Company X, 2021). Besides social audits, the case company also expects suppliers to have certifications and standards in place targeted at environmental sustainability and quality in the form of policies and concrete goals, with the aim to reduce their impact on the environment and to ensure that the products are safe and are of quality.

The case company ensures supplier compliance with both social and environmental requirements through continuous monitoring and negotiations (Company X, 2020). Doing business as a supplier to Company X Sweden can be done at the regional level as well as the national level. In the path of digital transformation, the case company has introduced the new supplier portal aimed at improved collaboration and exchange of information between the company and suppliers. The company strives to meet industry standards established by GS1 Sweden (i.e, GS1 standards help companies to have global business language) as this system assists the company to enable e-commerce, warehouse management, and logistic functions (Company X, 2021).

The case company selects suppliers in three ways namely, to do business directly with the store, with the company's order portal for local suppliers, and as a central supplier (Company X, 2021). In order to do business directly worth the store, the supplier selection process consists of four steps, in the first step, a self-declaration is submitted by the potential supplier containing company details, the application is being reviewed by the company, and approval or rejection decision has been made. After getting approval, stores can apply for supplier's declaration (Company X, 2021). Finally, the supplier directly contacts the store to conduct business operations. In the second category, for local suppliers, an order portal has been used to manage data for stores as well as for suppliers. For the third category, the case company selects and runs central suppliers through the category manager. The requirements to become a central supplier includes a sales plan as well as the capacity to deliver to a certain number of stores (Company X, 2021).

3.2.2. Interview

The primary data source used for this study was a semi-structured interview method with the purpose to investigate machine learning readiness in the supplier selection process. The desired outcome of the interview process largely depends on the purpose of research, interview dynamics, context, and choice of methods (May, 2011; Bryman, 2012). The authors decided to conduct a semi-structured interview method to explore machine learning readiness in the supplier selection process. An overview of this interview is displayed below in table 4.This interview method was deemed to be useful because the interview questions are generally specific, which allowed the interviewee to respond in a rather flexible manner and it also allowed the interviewers to ask follow-up questions which allowed for a more organic discussion (May, 2011).

The main data collection technique that was used in this research study was a semi-structured interview. Secondary data sources, such as academic journals, were included as they were strongly applicable to the study (Bédard & Gendron, 2004). Interviews are an effective way of collecting data for a qualitative research study, especially because it offers greater insight than gathering information from secondary research to better understand a company and its processes (Bédard & Gendron, 2004).

As stated previously in chapter two, the literature review provided the main directions for the interview phase. Therefore, various interview questions have been formulated on the basis of existing relevant literature (i.e., previous research, academic articles, or frameworks). Simultaneously, it also helped to formulate an interview guide containing the list of topic-specific questions to be asked in the interview (Bryman, 2012). The interview was conducted in April 2021 and the interviewee is an automation expert at 'Company X'. Due to the COVID-19 pandemic, the interview has been carried out through Microsoft Teams as it was not possible to conduct interviews in person.

In order to gain a holistic view of the case company's practices regarding the supplier selection process and ML readiness, the aim of the interview study was to obtain information about the company's processes and procedures. Prior to starting the interview, the interviewee was informed about confidentiality and anonymity of the interview process through both e-mail contact and an oral agreement before asking the questions. The initial phase of the interview phase was focused on general questions aiming to discover more about the role and responsibilities. After this, questions related to the supplier selection process were asked to the interviewee, which was followed by questions on ML readiness in the supplier selection process in accordance with the theoretical framework in section 2.6. After the interview, the researchers started transcribing immediately after for the reason that the answers and contexts would be understood better, and a follow-up could be arranged as soon as possible.

Interviewee	Date	Interviewer(s)	Topic	Length/duration
Automation Expert	22/04/2021	Nazish and Afra	A semi-structured interview on 'Company X'	50 minutes

Table 4. Overview of Interview

3.2.2.1 Interview Sampling

A purposive sampling approach has been used for this research paper based on the suitability to our research purpose. In order to start the primary data collection, the authors of this study did research on various companies that they found interesting. This was based on current trends in technology, but it also depended on factors such as company size and geographical location. The idea that the researchers had was that various employees - preferably with different roles and job positions within the same department - were going to be interviewed. The departments that were selected were procurement and/or purchasing (depending on the company size and structure). No distinction was made when it came to the amount of experience as the authors deemed all views as valuable for the research. Also, demographic traits such as gender were not considered as these types of distinctions are not deemed as significant for this particular research paper. In case of this study, the interviewee is deemed as an expert as this is the field the participant is knowledgeable about and has many years of experience in. Hence, this was the main reason for the researchers to select this participant for this research paper. The authors believed that comparing practical experiences would be complementary to the literature that was done prior to the interviews. The setting in which the participant was interviewed was Microsoft Teams.

3.2.3. Documents

Documents as secondary data were a valuable source of information that provided additional support for data collection. The prime objective of gathering documents was to gain insight into case company history and background which is presented in chapter 1 and to understand machine learning readiness in the selection process at the case company. In addition, these documents supported the theoretical foundation that was accumulated through interviews with the employee of the case company. As May (2011) reported that the analysis of documents not only includes researchers' subjectivity but also the social context of the research sample.

In order to ensure the quality of documents and the importance of the social scenarios in which they are written, the focus of this research is to retrieve documents directly from company sources. Specific documents that the authors analysed were an annual report, a quarterly report and company case studies. To complement the digital company documents, the company's website allowed the authors to access specific web pages and blogs. In addition to the documents, the authors also made use of other online sources such as topic-relevant videos to ascertain the credibility of data collection as well as data saturation. It is evident that the company documents and videos generated a significant understanding of the case company's systems, procedures, and processes. Table 5 below displays an overview of the most valuable company documents and videos. It is observed that the company documents and speakers from the videos all address topics such as technology, innovation, digitalisation, and the company's suppliers.

Name	Year	Topic	Length/duration
Company Documents			
Company X	2020	Annual report	137 pages
Company X	2021	Quarterly Report	7 pages
Company X	2021	Supplier’s portal	Not applicable
Company X	2021	Webpage on data protection	Not applicable
Company X	2021	Company blog on own suppliers	Not applicable
Company X	2021	Webpage on innovation	Not applicable
Company X	2021	Webpage for existing suppliers	Not applicable
Company X	2021	Webpage on the supplier selection process	Not applicable
Media company, focused on technology and media	2019	Article on ‘Company X’, intelligent solutions and purchasing.	Not applicable
International event service provides focused on business events	2021	Webpage on ICA as a case study. Focus on a company becoming a data driven retail organisation.	Not applicable
Videos			
Speaker 1	2020	Panel presentation and discussion on the future of retail, digital development, and artificial intelligence.	40 minutes
Speaker 2 & 3	2019	Panel presentation on data innovation and self-service analytics. More specifically, what the company has learnt, achieved, and future strategy.	20 minutes
Speaker 4	2019	Panel presentation on innovation solutions such as machine learning and experiments.	20 minutes

Table 5. Overview of Company Documents and Videos

3.3. Data Analysis

This section of the chapter consists of examining the methods above in section 3.2. The data collected through the primary and secondary sources were analysed in order to answer the research questions that were stated in the first chapter. The purpose of the data analysis phase is to reduce the large amount of collected data, and make it more meaningful and comprehensive (Bryman, 2012). This particular examination can be defined as the categorisation of the amount of data collected into various sub-sections which intends to determine the quality of the gathered data (Yin, 2003). Once this was done, the authors were able to seek patterns and draw preliminary conclusions based on the categorised findings (Bryman, 2012).

The objective of the analysis for this paper has been to present machine learning readiness in the supplier selection process at 'Company X'. For this study, the authors recorded the interview and transcribed this straight after, which enabled the research to standardise and analyse the data based on the theoretical framework (section 2.6) which provided the basis for data analysis. In order to analyse company documents, reports, and relevant videos, the authors conducted a content analysis aimed to classify the data into categories and present them in a systematic manner (Bryman, 2012). The authors repetitively moved back and forth between data collection and analysis due to the iterative nature of the data analysis process.

The first step of the data analysis was to analyse relevant literature on the topic of ML readiness in the supplier selection process. By starting with this step, the authors were able to identify what foundations were laid in academia and could act as a sort of benchmark for companies in the retail industry. Additionally, the literature review established the basis for this research and the authors were able to identify research gaps in the literature which led to formulation of the interview questions.

The second step of the data analysis was to create an interview guide which was used as a guideline for the semi-structured interview with the case company. The interview guide consists of questions that were created after writing the literature review, which allowed the authors to take into account different points of views and learn more about the chosen topic and related subjects. The interview guide helped to explore the field with the perspective of actual practice.

The third step was to go back to the literature review and check whether some questions could be tweaked, added or deleted in order to maintain a focussed scope. This allowed the researchers to formulate a specific set of questions in order to be able to attain valuable information from the interviewee.

After conducting the interview, the transcribing process was also done shortly after to ensure that the nuances were also taken into account. After the transcribing process, the company interview was coded. Similarly, the authors also coded all the relevant company documents. This provided the authors with a clearer overview of the data. Lastly, once the coding process was completed, the authors were able to notice similarities and differences. Together with the relevant literature, the findings of the interview and content analysis were analysed thoroughly.

3.4 Critical Evaluation

3.4.1 Reliability

The reliability ensures that the results and findings are identical if the research would be conducted again with the same procedures (Ellram, 1996; Yin, 2003). Ensuring reliability is of essence when conducting research as it enables others with a similar interest to be able to replicate the same research so that they are able to achieve similar results (Flick, 2014). In addition, the reliability aims to reduce research bias and inaccuracies (Yin, 2003). Thus, it is important for the authors to consider this concept and its related practises to maintain transparency (Flick, 2014).

In order to fulfil this criterion, the data collection methods were designed in a well-structured manner by recording the participant, taking notes as well as categorising the data based on theoretical framework. This meant that the authors ought to consider the reasoning behind and with what ways this research paper is carried out (Flick, 2014). In fact, the authors shared the interview guide in order to provide the reader with transparency and a deeper understanding of the research (Flick, 2014). The interview protocol consists of 14 main questions. However, the authors also prepared a few follow-up questions in order to increase the chances of receiving holistic answers. This research paper is based on the relevant literature found in academic journal articles and books, which helped the authors to build and accumulate a foundation to complement the data collection phase and to complete the rest of the research paper.

3.4.2 Validity

Another important aspect of conducting research was to ensure validity which deals with the integrity of the research results and can be measured through internal and external validity (Flick, 2014). Internal validity refers to the findings of the authors, in which the theoretical foundation was accumulated in the literature review (Bryman, 2012). According to Yin (2003) the problem of making inferences is a major concern in the case study research. For this study, the authors attempted to ensure this criterion with the help of the theoretical background that has been used to analyse the data derived from the interview and content analysis. Moreover, in order to avoid errors or ambiguity in answers, the researchers aimed to structure the interview guide in an understandable manner.

External validity refers to the accuracy of the research results and to the fact that this research is able to be replicated in order for the results to be generalised (Ellram, 1996; Bryman, 2012; Flick, 2014). Meaning that if the research is externally valid, then it can be applied to the general population instead of focusing on one target group that is under study. In this particular case, the authors are able to contribute by accumulating previous literature and complementing that with the collected data from the case study. According to Yin (2003), a case study enables researchers to generalise as one is able to learn from one particular case and apply it to other similar cases. For this research, it implies that ML readiness in the supplier selection process is also applicable to the other companies in the retail industry. Moreover, it also reflects that the research results can be applied to other industries.

3.5 Ethical considerations

Ethical considerations are imperative to maintain the integrity of the research as well as to protect research participants (May, 2011). In the course of carrying out this study, various ethical deliberations and considerations were taken into account. This was reflected in ensuring that the data collection process was in line with aspects such as consent, confidentiality, and the freedom to change their minds in regard to the given answers and participation. Henceforth, the participant was given a brief introduction to the research topic and core ideas including study purpose, and the research process to ensure consent. Additionally, to assert confidentiality by informing the participant about recording the interview for the process of transcribing, provided anonymity to keep the identity hidden and to make the participant aware that the recording would not be shared with third parties. Furthermore, the researchers assured that the retrieved data would be protected without causing any personal harm.

During data collection through a semi-structured interview for example, it is important to consider informal evidence for the reason that the authors should be prepared to ask follow-up questions as this enables the authors with new insights and provide an indication of the credibility of the information that is given (Scapens, 2004). Meaning that all the 'informal evidence', such as body language, tone of answer, casual comments, etcetera, should be noted, on the condition that the interviewee gives consent (Scapens, 2004, p. 267).

3.6. Critical Reflections on the Research Methods

3.6.1 Interview

When conducting a (semi-structured) interview the authors of this research paper countered various aspects that they took into consideration. As the interview was transcribed into transcripts, this means that the data was reduced to a transcript and the transcript is solely used as an instrument for interpreting what has been said by the interviewee (Flick, 2014).

Also, one should always remember that the researcher can never be sure of the fact that the given answer is true, as the interviewee is able to give the 'desired' answer. However, this could also be done unintentionally, the interviewee is then able to provide a narrative and not necessarily a representation of universal facts (Flick, 2014). Thus, the narrative can be seen as a framework in which experiences are put in (Flick, 2014). Another important aspect when analysing the data, is that what is said by the interviewee is interpreted correctly. Overall, another important aspect that should be taken into account is the fact that the researchers had an intended audience in mind when writing this study. Which means that it is written from a certain point of view, in a specific way in order to make it understandable for the reader.

Another challenge that the authors faced was finding a suitable company and more specifically, interviewees who had the time or were willing to participate, which many said was also due to the current pandemic and a shortage of staff. This aspect was reflected during the interview process, as the interviewee cut the interview short due to a busy schedule. This meant that the remaining questions had to be answered through email. Lastly, because the interview was semi-structured, it sometimes occurred that the interviewee gave more examples and took more initiative to provide the authors with information. The researchers then had to find the right balance to steer back the conversation by asking the right follow-up question.

3.6.2 Document Analysis

A limitation with document analysis is that the authors were limited to the accessibility of secondary sources due to the current pandemic as well as restrictions regarding confidentiality. Then, of course, the subjectivity of the authors was also a limitation when analysing the interview results and content analysis in the findings and discussion.

3.7 Summary of Methodology

Methods	Specifications
3.1 Research Philosophy and Approach	3.1.1. Research Philosophy 3.1.2. Research Approach
3.2 Research design	3.2.1. Literature Review 3.2.2. Single Case Study 3.2.2.1. Introduction to the Case Company: 'Company X' 3.2.2. Interview 3.2.2.1. Interview Sampling 3.2.3. Document
3.3 Data Analysis	Primary data: semi-structured interview Secondary data: content analysis of company documents and videos
3.4 Critical Evaluation	3.4.1. Reliability 3.4.2. Validity
3.5 Ethical considerations	Ensuring consent and confidentiality, and anonymity.
3.6 Critical Reflections on the Methods	3.6.1. Interview 3.6.2. Documents

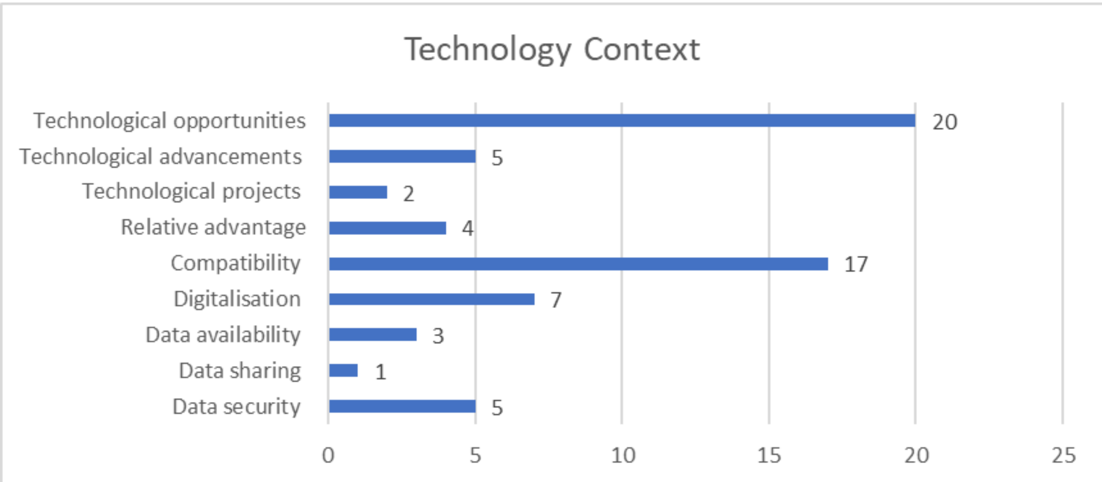
Table 6. Summary of Methodology

Chapter 4. Findings

This chapter will present the results of the data collection process. This chapter will be divided into 4 sections which are based on the 4 major coding themes and their related components. This will be done through the following parts: section 4.1 will present the results connected to the first theme: technology. Then, section 4.2 will present the second major theme findings, namely, organisation. This will be followed by the results in accordance with the third major theme in section 4.3: environment. Lastly, in section 4.4 the findings of the fourth major theme, barrier, will be presented. Moreover, the major themes that were used in the coding process will first be explained in order to provide the reader with general context including the identified components. The findings consist of empirical data which is retrieved from an interview transcript with the case company and content analysis of company documents and videos to provide a better understanding to answer the research questions in the following chapter. A total of 34 codes were given to 293 statements. Some statements were given multiple codes due to overlapping contexts.

4.1 Technology Context

This major first theme, technology, consists of 9 related codes which the authors of this research paper extracted from the empirical data (company interview and content analysis of company documents). Graph 1 below displays an overview of the first major theme and the related codes from the initial coding procedure. Moreover, the initial codes that are linked to technology, are a total of 9 and are the following: technological opportunities, technological advancements, technological projects, relative advantage, compatibility, digitalisation, data availability, data sharing, and data security. The total amount that all these 9 codes were linked to statements were 64 times. The technology related codes were given in accordance with the empirical data.



Graph 1. Technology Related Codes and Repeatability

4.1.1. Technological Opportunities

As the illustration above depicts, with a score of 20, ‘technological opportunities’ is the code that was given the most. This notion relates to a company’s ability to recognise technological opportunities by being knowledgeable of what the added values are of adopting, implementing, and optimising technological innovations. The focus here is on being up to date and the acknowledgement of the changing environment (e.g., digitisation) and the understanding to encompass the opportunities and usefulness of adopting technological tools such as machine learning. The empirical data revealed that although 'Company X' does not use machine learning in the supplier selection process, they in fact do acknowledge the benefits of implementing it for sorting out smaller vendors and the inevitability that more processes will become automated in the future. Especially, through the usage of digital colleagues. The company is aware of added benefits such as reduced costs, more efficiency, and improved quality of processes and what they are able to offer their customers when automating manual tasks.

The empirical data also revealed that the rate of change within 'Company X' is high and that it tries to increase internal efficiency and increase product offerings through various digital initiatives which all involve the usage of data, automation, and artificial intelligence (Company X, 2020). Moreover, the researchers of this thesis discovered that 'Company X' is aware of the changing environment in the retail industry and acknowledges that this entails that changes are in place, not only for the industry that they are active in, but also for them specifically. Besides 'Company X' being up to date regarding technologies that fit the changing environment, the authors were also able to notice that much of the data from the content analysis and the case interview can be connected to the company's knowledge on the specific applications and ability to understand the added benefits.

4.1.2. Technical Advancement

The second code on graph 1 shows that 'technical advancement' has a score of 5, meaning that the authors connected this code to a statement 5 times. As the name gives away, technological advancement refers to a company being able to truly understand a certain technology and being able to implement and improve it to optimise processes. 'Company X' is aware that artificial intelligence, and in particular, machine learning is becoming more commonly used applications, which leaves room for advancing the applications of technology. At the moment, the company uses it for purchasing and assortment planning as it enables them to anticipate demands and trends in a more efficient manner. The empirical data also revealed that the company makes use of machine learning tools for digital assistance in the form of intelligent chat bots (interviewee, 2021). In addition to that, 'Company X' is also testing small humanoids, in some of their bigger stores (IDG, 2019). Moreover, it is all part of the company's strategy, in which they specifically focus on becoming more data driven with the support of artificial intelligence to eventually reduce costs and improve their technological competences (Company X, 2020).

4.1.3. Technological Projects

The third code in graph 1 depicts that 'technological projects' has been assigned to 2 statements of empirical data. This particular code refers to the company encouraging technological innovation and development. In the case of 'Company X', the empirical data revealed that this can be linked to the fact that they have an innovation hub which is focussed on their own digital development projects and collaborations with external parties (Company X, 2021). Through these development projects that are aimed at technological innovation, the company aims to enhance the advancement of digital innovations at the company at a quicker pace (Company X, 2021).

4.1.4. Relative Advantage

The code 'relative advantage' was linked to statements 4 times. This is a code that originally belongs to the TOE-framework by Tornatzky and Fleisher (1990) and refers to the ability of a specific technological innovation to provide a company with more benefits than it would otherwise (e.g., manual work) or in comparison to technological innovations. For example, the content analysis revealed that speaker 1 (2020) provides an example in which he explains and shows that artificial intelligence is just as capable, 'if not better than a human', of designing a poster as the difference is very minimal. Moreover, the empirical data shows that 'Company X' has a great awareness of the benefits of intelligent applications and adopt an active approach when it comes to taking action. The statement below reflects this standpoint:

''Artificial intelligence and analytics are an efficient way to reap benefits and thus, extensive investments are made in both areas. Artificial intelligence represents a shift that enables the company to deliver more value to all customers as well as positively affect upstream processes such as sourcing. Advanced analytics will make it possible to predict and anticipate in a completely new way'' (Company X, 2020).

The empirical data shows that the company is able to benefit from an advanced form of analytics with the adoption of artificial intelligence. The company is investing in advancing these innovations in order to use artificial intelligence and digitised data to analyse large data sets and handle more complex issues, transform their way of working, and the way they interact with stakeholders. Moreover, automating certain processes allows the company to be more efficient and save costs (Interviewee, 2021).

4.1.5. Compatibility

The second most given code by the authors of this study is 'compatibility' as this was linked to statements of empirical data 17 times. Similar to the code 'relative advantage', this is also a code that originally belongs to the TOE-framework by Tornatzky and Fleisher (1990) and refers to the importance of perceiving a compatibility between the company's practises and the need for adopting a certain technological tool such as machine learning. The empirical data revealed that 'Company X' does not utilise machine learning in the supplier selection specifically, however, a mix of Oracle Policy Automation (OPA), a cloud service, and machine learning applications as are used to optimise other processes (e.g., logistics) within the company's supply chain. When 'Company X' was asked whether their supplier selection process strategy would be compatible with machine learning applications, the interviewee (2021) stated ''Yes on that''. After the interviewers asking the interviewee how this would be done, the interviewee (2021) stated the following:

"Absolutely. It would be good to automate a part of the selection. Perhaps not the bigger ones, but the smaller vendors because it could be hard to handle suppliers that would be interested in supplying to (company X). It can be hard to handle all the suppliers that really like to join in, but their size could be a concern" (Interviewee, 2021).

Although 'Company X' is a large retail company, the interviewee (2021) stated that the size of the company is not necessarily significant to being able to adopt and utilise machine learning applications by stating the following:

"(...) start-up companies doing their own machine learning models as well as digital assistants that are helping with negotiations as well as bigger platforms that at least try to go in that direction using the capabilities of machine learning. So, I think that it is broadly used in big companies and smaller ones, in different ways" (Interviewee, 2021).

4.1.6. Digitalisation

The code 'digitalisation' was given a total of 7 times to statements from both the content analysis and the case interview. This notion relates to the usage of digital technologies and data and is able to drive digital transformation. For 'Company X', this is part of their strategy. Their annual report revealed that they aim to reduce costs and enable integration through digitalisation (Company X, 2020). The interview revealed that 'Company X' has ''digital colleagues'' for certain processes such as digital assistance in the form of chat bots (Interviewee, 2021). An important note here was that the interviewee (2021) stressed the importance of big resources in order to be able to realise this:

''Digitalisation of retail requires large upfront investments in infrastructure, systems and competences – scale matters'' (Interviewee, 2021).

It is clear that 'Company X' understands the need for especially financial resources, as they heavily invested in IT two years ago and planned for automation and e-commerce to be next back then (IDG, 2019). IDG (2019) stated that with 'Company X' having a market-leading position, the company has favourable conditions to further drive and advance digitalisation.

4.1.7. Data Availability

The code 'data availability' was linked to the empirical data 3 times. As the code already reveals, this notion refers to the fact that a company has accessible and valid data ready to be used. For 'Company X', this begins with having loads of data available and it seems that this is not an issue as Speaker 1 said the following:

''But when we see data on the scale of (Company X) (…) imagine the amount of data'' (Speaker 1, 2020).

While speaker 1 (2020) presented about the importance of data accuracy and trust in its ability to produce data that can be trusted, the presentation said the following: 'Your AI is as smart as your data', which corresponds with what speaker 4 (2019) stated about needing sufficient data in order to be able to increase the level of accuracy when it comes to the outcome or decision. Meaning that the amount of data is what contributes to the intelligence of artificial intelligence (Speaker 1, 2020). 'Speaker 4 (2019) adds that data availability is not self-evident for the reason that it is rather a lengthy process to collect or access data, but the availability of data is of importance as it adds to data accuracy over time (Speaker 4, 2019). For 'Company X', the availability of data does not seem to be an issue as it seems to have a lot of ''gold'' as speaker 3 (2019) phrased it, referring to the amount of data that the case company has. However, trust and reliability are important elements and are strongly connected to this code are what should be focused on as this is what might pose a challenge in the development of automation (Speaker 1, 2020).

4.1.8. Data Sharing

The code that was given the least, 1 to be exact, was 'data sharing'. This code refers to a company being able to share data, ranging from departments to subsidiaries being able to share data with a mother company for example. In the case of 'Company X', this means that the company is being able to share data with other departments within the supply chain, but also with other stores that fall under the same subsidiary. 'Company X' experienced benefits of integrating departments in order to stimulate the sharing of data. According to the director of analytics, this has been a rather fruitful outcome and has stated the following:

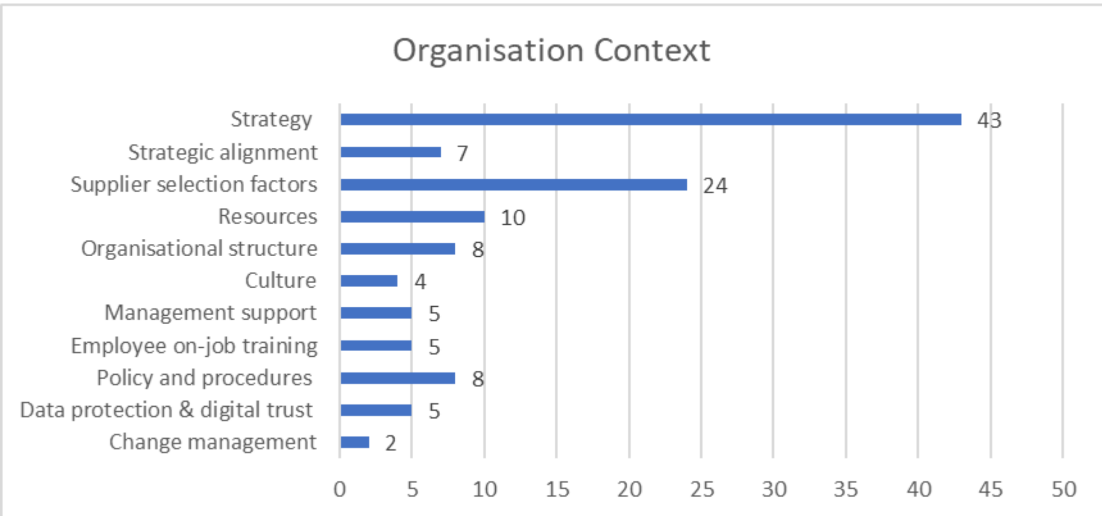
"We did it together. Business, IT and Analysts never worked so close before. The transition is still ongoing, but the amount of change they achieved is tremendous" (Speaker 3, 2019).

4.1.9. Data Security

The authors of this study linked the code 'data security' to the empirical data a total of 5 times. This code refers to the practise of protecting digital data by using technological tools. The 2020 annual report of 'Company X' reveals that they are aware of IT related risks and have produced an updated security strategy to protect digital data for all kinds of harm related to abuse, unauthorised access, inaccessibility, and loss (Company X, 2020). Since the retail company consists of subsidiaries and shares digital data between the retail stores, these companies carry a joint responsibility for safeguarding that data is handled in a secure and correct way. This is done by having specific agreements and arrangements in place to ensure the security of data (Company X, 2021). The empirical data also reveals that the company has a group-wide privacy office to ensure that its employees are aware of data security laws and that the collecting, storing, and sharing of data is done according to those specific policies and laws (Company X, 2020). Moreover, the case company acknowledges that a key aspect of data security is the administrative structure (Company X, 2020).

4.2. Organisation Context

The second theme, organisation, has identified a total number of 11 codes, which accounts for 121 statements, depending on the frequency of these codes in the interview and the company documents and videos. Graph 2 below displays the identified components along with the frequency of usage in the coding process. Organisational context is crucial in adopting ML for the supplier selection process since organisation related components were mentioned most times during the interview and in the content analysis. In the case of organisation context most repeated codes were grouped as follows: strategy, supplier selection factors, resources, strategic alignment, organisational structure, top management support, culture, employee training, policy and procedures, data protection and digital trust, change management.



Graph 2. Organisation Related Codes and Repeatability

4.2.1. Strategy

The prime interest of the authors was to explore the factors that could impact case company readiness to adopt ML technology selecting suppliers. In this regard, it was interesting to notice that certain factors were closely related in the organisation aspect such as the 'strategy' which is one of the most repeated components in the coding process and can be linked to the other factor of 'strategic alignment'. The code of strategy was linked to the empirical data the most, a total of 43 times. The findings illustrated that the organisational strategy needs to include ML applications as a part of digital strategy in order to implement it across the whole organisation. Thus, the company aims to adopt innovative technologies such as ML not only for selecting suppliers but at all levels within the company. Exactly as the respondent mentioned during the interview that implementing innovations is an important part of the company's 'strategy', the following quotes represent this statement,

"I would say that the strategy is to use it broadly within the organisation of Company X" (Interviewee, 2021).

"Company X does this on a strategy that is implemented across the whole company" (Speaker 1, 2020).

It can be seen from the above statement that the organisation components are imperative to support the new technology adoption process. Besides the existing digital strategy, the authors also noticed the future automation strategy, concerning a path to follow in the future. The case company aims to apply machine learning across the whole company including the supplier selection process and maintain the leading position in the market which is explicitly evident from the content analysis finding.

''Currently, the company has been using AI and ML to plan purchasing and assortment which could help to understand future needs'' (IDG, 2019).

4.2.2. Strategic alignment

strategic alignment is connected to the above stated component 'strategy' and in empirical findings this code was assigned 7 times by authors. In addition to this, findings demonstrated in detail how a company aligns its digital strategy within the whole enterprise. Since the successful adoption required the development of certain capabilities, people cooperation, and data governance across the whole enterprise. This is presented by below mentioned quotes.

"We are working with automation of this type of capabilities in all operating companies. We are using it in logistics and assortment of buying in procurement, in marketing, and finance. (…) So, we are using the capabilities across all the functions" (Interviewee, 2021)

"(…) We started the transformation from an enterprise perspective from the very first day, involving all business units within the company, working closely with IT and analytics, while at the same time focusing on all three aspects of people, process, data and technology" (Speaker 3, 2019)

4.2.3. Supplier selection factors

The 'supplier selection factors' is the second most repeated component in the coding process, and the authors gave this code in total 24 times. However, when the authors brought up the notion of using ML for selecting suppliers the interviewee explicitly stated that presently, they are not using any ML application in the supplier selection process. Findings reflected that the assortment and buying of the procurement organisation is responsible for selecting a supplier that has some predetermined factors or criteria based on the product categories. Furthermore, it is evident from the interview that the case company considered ML technology as essential for processes efficiency and they are ready to adopt ML for selecting suppliers but right now this is not on the agenda of the digital strategy. The following statements describe these arguments:

"If we go into the specifics of the supplier selection process, I will say that we do not have any direct relations in regard to automation" (Interviewee, 2021).

"There are many factors, it depends on the category. But I would say that it is not a single point such as the price for example, but rather a mix of different components, …but also the importance of corporate responsibility, carbon footprint of CO2 emissions, or climate perspective, as well as Sweden versus other countries" (Interviewee, 2021).

"I think that this is a must. If it is going to be automated, we will bring some algorithms into place to do the work and do the selection" (Interviewee, 2021).

4.2.4. Resources

On the question whether 'Company X' provides resources (e.g., financial means or in the form of training to employees) to enable technological innovation within the supplier selection process it is clearly illustrated that the case company has been facilitating automation regardless of the nature of the tasks. The above-mentioned graph illustrates that the notion of resources has been allocated 10 times to the research findings. By adopting an enterprise approach for digital transformation, the prime focus of attention is people, partnerships, technology, and data. At the case company, the investment rate is very high in terms of IT and digitalisation (Company X, 2020). This is indicated from the below statements taken from the interview and content analysis.

"I would not say that it is specific to the supplier selection area, but rather as a broader perspective and areas that we work with" (Interviewee, 2021).

''It is all about the people and the partnership and a lot about 'gold' (i.e., data)" (Speaker 3, 2019).

4.2.5. Organisational Structure

During the coding process, this code was given to empirical findings 8 times. From an organisational perspective, 'organisation structure' is an important component in the adoption of ML technology since it can directly influence the organisation's adoption decision and process. The findings depict that 'Company X' is a big enterprise operating widely at the national and international level as well as that it is an old company in terms of the structure. Therefore, the speed of innovation adoption could be slower in comparison to smaller companies such as start-ups for example. In addition, as companies grow bigger, they need to build new structures and foundations in order to be compatible with innovative technologies as well as maintain operational efficiency and high service levels. Below mentioned quotes explain these arguments.

"Yes, I believe that we are a pretty big one. So, that, normally, takes longer to move and also the structure that we have" (Interviewee, 2021).

"We need to build a foundation for our innovation (…)'' (Speaker 4, 2019).

4.2.6. Culture

The notion of culture was linked to the empirical findings 4 times. 'Company X' has a 'culture' of continuous learning and improvement. By building new learning platforms, structures, and a strong partnership with people, the case company exhibits the ability to share knowledge and learn new things. The following quotes support these arguments. This culture of continuous learning and constant change allows the company to cope with dynamic conditions and market trends in order to achieve competitive advantage (Company X, 2020). This can be illustrated by the following claim.

"We are working to keep up with new things that are happening" (Interviewee, 2021).

4.2.7. Top Management Support

The interview respondent addressed some other important components that are comparative less repeated codes in comparison to the above-mentioned components such as 'top management support' and commitment deemed critical to the readiness to adopt ML, therefore it should be part of the long-term strategy to remain consistent. The authors have given this code 5 times in the coding process. At a strategic level, the case company aims to create digital capabilities in collaboration with other companies and also working on individual projects which indicate that top management support and leadership is imperative for successful ML adoption (Company X, 2020).

4.2.8. Employee On-Job Training

The notion of 'employee on-job training' was linked by the authors to the findings a total of 5 times. In addition, these findings depict the support of management for 'employee on-job training' and internal education. 'Company X' invests in the education and extensive training of data managers or analysts in order to enhance technical expertise as well as build skilled teams across departments to ensure system integration. The below statement describes the notion.

"(…) we need to have cross-functional teams with data scientists that can focus on the brilliant insight, building artificial intelligence, machine learning and, statistical models in the right context" (Speaker 4, 2019)

4.2.9. Policy and Procedures

Following this, the component of 'policy and procedures' was included 8 times as code during the coding process and it also connected to the organisational structure component. It is found out from the interview that some of the subsidiaries are frontrunners in terms of innovations to create new opportunities for the business. The case company conducted the business operations in an organised manner by using certain procedures, criteria, and cooperation across departments to ensure efficiency, and effectiveness (Company X, 2021). The company also focuses on continuous improvement and learning, discovering new potentials to expand business operations and maintain brand market position. In doing so, the policy is people-focused which involves motivating people and preparing them for value-added activities (Company X, 2021). Furthermore, it is done through certification of these different processes in the value chain including sourcing (i.e., supplier selection), logistics, distribution, and so on to ascertain the market standards. The statements below provide a further illustration of these statements.

'The company also follows the policy of continuous improvement with regards to innovation, exploring new options, producing new opportunities to enhance business operations and ultimately business value' (Company X, 2021)

'All suppliers at the company are quality-certified who have gone through certain quality control processes and obtained the company's quality standard certificate' (Company X, 2021).

4.2.10. Data Protection and Digital Trust

Another notion that authors wanted to bring up is 'data protection and digital trust' which refers to a company's ability to handle (personal) data correctly to provide digital trust as this is a critical part for the overall image of a company. Furthermore, it also helps to improve brand value and market position of the company. This code has been given to the empirical findings a total of 5 times. '*The case company strives to protect personal data in an optimal way to ensure digital trust which is vital for digital transformation' (Company X, 2021).* An aspiration that the case company has is to process data in accordance with the industry data protection laws and also comply with the company's data protection rules and procedures. Furthermore, all retail stores process the personal data in coordination with the other subsidiaries of the case company within EU and EEA countries, however in the case of outside EU data access, the company ensures the data protection through "data transfer agreements" (Company X, 2021).

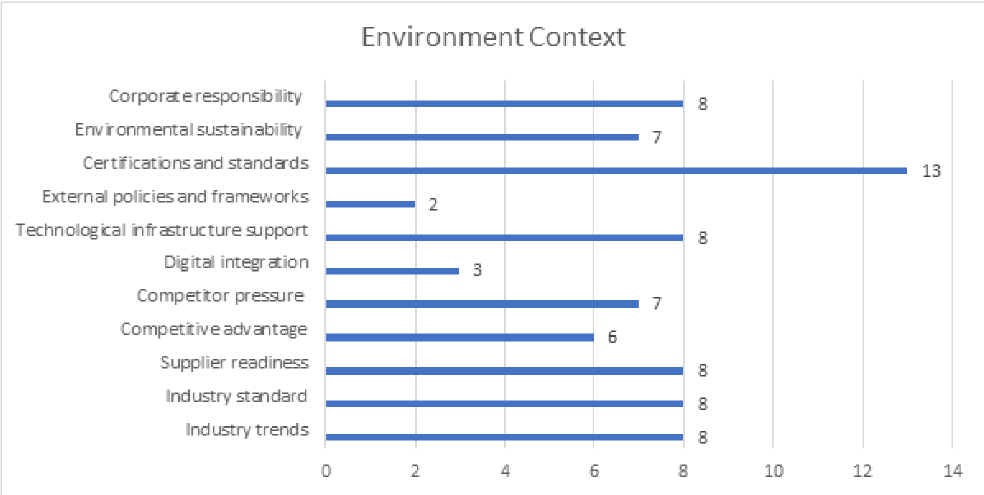
4.2.11. Change Management

The code of change management was linked to the empirical data the least, in total of 2 times. It stated that the fast-paced change and rapid technological innovations are driving organisations to formulate a responsive strategy towards changing market conditions. It is noted by the authors that the case company is also operating in a dynamic market, and it is essential to be responsive, and adaptive towards digitalization and automation in order to gain a competitive advantage. The case company has been adopting innovative technologies such as ML applications in various business processes for example in waste management or logistics and also ready to implement it across the whole organisation to ensure efficiency. However, these disruptive changes are required to be managed in an organised and structured way and involves preparing and supporting employees to successfully adopt change in order to maximize benefits. Likewise, empirical findings indicated the challenges of digital transformation are that people do not trust AI outcomes that it can perform in a more efficient way than traditional approaches. "So, we spend a lot of time in change management, and we have spent a lot of time doing the use cases where everyone thought it would be impossible to use AI'' (Speaker 1, 2020). Thus, trust is a critical factor to adopt innovations and it can be linked to the technology, but it also depends upon the company how they communicate and prepare people for ML applications. The following statement presents this notion.

"(…) we need to understand it as well, from the algorithmic models to really have trust that it actually works. So, also the confidence in the program and these kinds of capabilities from our part" (Interviewee, 2021).

4.3. Environment Context

This third theme is environment and consists of 11 related codes which the authors of this research paper extracted from the company interview and content analysis of company documents. Graph 3 below displays an overview of environment related codes from the initial coding procedure. Moreover, the initial codes that are linked to the environment context are the following: corporate responsibility, environmental sustainability, certifications and standards, external policies and frameworks, technological infrastructure support, digital integration, competitor pressure, competitive advantage, supplier readiness, industry standard, and industry trends. The total amount that all these 11 codes were linked to statements was 78 times. The environment related codes were given in accordance with the empirical data.



Graph 3. Environment Related Codes and Repeatability

4.3.1. Corporate Responsibility

The first code illustrated in graph 3 Is 'corporate responsibility' and has been linked to 8 statements of this study's empirical data. Corporate responsibility refers to a company's practises and whether these comply with a wider range of social issues, such as human rights and environmental responsibility. Moreover, it considers the impact that an organisation has on society and the ecosystem. The empirical data revealed that 'Company X', has a global network of suppliers, which entails that their responsibility encompasses Sweden (Company X, 2020). For 'Company X', this means that their suppliers also need to meet certain requirements for them to be able to meet certain goals. For example, the case company reached its climate neutrality target in 2020 and has been able to decrease greenhouse emissions per square meter by approximately 75% by improving aspects such as a better logistics flow and energy (Company X, 2020). This also means that their suppliers undergo social audits in order to check whether they meet the requirements that are in place (Company X, 2020). It appears that 'Company X' conducts assurance procedures for their own brand as the majority (approximately 90%) of their suppliers are located in what they call 'high-risk countries'. and does this regularly to check whether the supplier has maintained the same level, when the audit was done at the end of 2020, approximately 85% succeeded and passed the re-audit. In this way, 'Company X' is able to ensure both quality and social responsibility in its practises, specifically, when it comes to the sourcing and production area (Company X, 2020). The importance of criteria also reflects in what the interviewee said about corporate responsibility, namely:

"There are many factors. There is price as a factor, but also the importance of corporate responsibility, carbon footprint of CO2 emissions, or climate perspective, as well as Sweden versus other countries" (Company X, 2020).

The above-mentioned statement illustrates that corporate responsibility is one of many factors that is taken into account when selecting suppliers.

4.3.2. Environmental Sustainability

The code 'environmental sustainability' is rather similar to the corporate responsibility code. However, the authors of this study have decided to include this code on its own as 'Company X' has a specific focus on this topic, and they also have special requirements regarding the environment for their suppliers. This code was given to statements throughout the empirical data a total of 7 times. The 2020 annual report of 'Company X' reveals that one of their main challenges will be linked to the effects of climate change and population growth and how this will eventually affect the availability, supply, and cost of a variety of goods (Company X, 2020). Nonetheless, the case company aims to not only have requirements in place for suppliers, but they also aspire to actively reduce their internal impact on the environment by enforcing environmental policies and targets for their own processes. As stated in the previous code (4.4.1), although suppliers are expected to monitor their own operations, in this case, to reduce their environmental impact, 'Company X' still conducts audits and follows-up to ensure that these requirements are met (Company X, 2020). For instance, 'Company X' has recently started a project with approximately 10 Asian suppliers and factories to reduce environmental impact when it comes to the label of 'Company X', as well as to ensure that the suppliers comply with the environmental requirements that are in place (Company X, 2020).

4.3.3. Certifications and Standards

The code 'certifications and standards' has been linked to the empirical data the most, namely, a total of 13 times. This code refers to suppliers needing to own certain certifications and comply with certain standards. For 'Company X' (2020), this means that suppliers should hold certifications for the environment, human rights, and quality to ensure the level of quality for the goods that they deliver. This also makes an important factor when selecting suppliers according to the interviewee (2021), in which he states the following:

"There needs to be a base level that is high enough, for factors such as hygiene factor, quality, climate, pricing. All of these need to be at a certain level, otherwise it is not relevant. You need to have a certificate etcetera, otherwise factors such as pricing do not matter" (Interviewee, 2021).

The statement above showcases that a basic level of certain criteria needs to be met, otherwise, there is not one decisive factor that can make the others obsolete or less important (Interviewee, 2021). Thus, it is of importance that the supplier complies to a certain standard (Interviewee, 2021). The specific type of certifications can differ and depends on the type of supplier (Company X, 2020). Also, in order to be knowledgeable on the topic and to be aware of the standards and certifications, 'Company X' has regular dialogues with other relevant external parties such as other players in the same industry and the authorities (Company X, 2020).

4.3.4. External Policies and Frameworks

The code 'external policies and frameworks' was linked to the empirical findings a total of 2 times. This code is also a code that originally is part of the TOE-framework by Tornatzky and Fleisher (1990) and as the name of this code suggests, this notion refers to policies and frameworks from external parties such as the authorities or investors. In the case of 'Company X', this means that they comply with the guidelines of the Organisation for Economic Co-operation and Development (OECD) for multinational companies and the International Criminal Court (ICC)'s anti-corruption principles for example. Complying with certain regulations from the government or other external parties, mean that there is also the opportunity for funding and investment to stimulate the development of technological innovations within the company. Just as there are certifications and requirements for the case study's supplier, there are similar requirements for 'Company X'. Examples of these requirements are often aimed at the environment, anti-corruption, data privacy, and human rights.

4.3.5. Technological Infrastructure Support

The code 'technological infrastructure support' was linked to the findings a total of 8 times. Again, as the name gives away, this code refers to the technological infrastructure of a company. For 'Company X', this is seen as an important part as this is key in maintaining and developing not only the data protection process, but also make it easier to manage through complex landscapes. It was especially the IT department that was an area that the case company invested heavily over the last few years, as this is a crucial part of the case company's strategy to increase integration between departments to bring together IT and analytics, as well as to increase the level of security (Company X, 2020). As mentioned prior in section 4.2.6 (see quote by interviewee), the systems and infrastructure need to be in place when wanting to develop digitalisation technologies in the retail industry (Interviewee, 2021).

4.3.6. Digital Integration

The code 'digital integration' has been linked to the data 3 times by the authors of this study. Digital integration refers to (parts of) the company being able to share information without being restricted due to the lack of applications and (information) systems. The benefits are that companies are able to work in a more streamlined and efficient manner due to a suitable infrastructure, enabling efficiency and more open communication. The following statement below will illustrate this:

Speaker 3 (2019) describes that a few years back, the business analysts active at 'Company X' were in essence working in silos, meaning that all the data was stored in silos and communication was not prevalent. She continued by saying that there was no strategy or standard way of working.

This statement reflects a lack of system integration since the respective areas worked separately from each other. Speaker 4 (2019) adds that innovation at 'Company X' is typically done in silos, which can lead to the rebuild of system infrastructures and disharmony, meaning that this can become a lengthy process.

4.3.7. Competitor's Pressure

The authors of this research paper linked the code of 'Competitor's Pressure' to empirical data for a total of 7 times. Similar to the codes 'relative advantage' (section 4.2.4) and 'compatibility' (section 4.2.5), this is also a code that originally is part of the TOE-framework by Tornatzky and Fleisher (1990) and can be defined to which extent companies feel pressured or intimidated by competitors. For 'Company X', this is an aspect that is realised as they work actively to produce new product lines in order to be able to offer their customers products. Meaning that the company works with many suppliers and both the acquisition and retaining of suppliers maintains an ongoing process (Interviewee, 2021).The interviewee (2021) continues by stating that it is the balancing of complying and the need to ensure that everyday operations are correct and smooth, whilst also needing to be up to date in regard to competition and their technological innovation and to a certain extent, also have a focus on the adoption and development of technological innovations. The interviewee (2021) stated the following about this:

"We need to comply and continue working as everyday operations. So, I think, we have both ways and we need to do both. We need to ensure that we are on top as of tomorrow, but also secure enough to deliver products to the consumers today" (Interviewee, 2021).

4.3.8. Competitive Advantage

The code 'competitive advantage' was linked to empirical data for a total of 6 times and refers to criteria that allow a company to produce and offer their goods (or services) for better conditions (e.g., price-quality ratio). In the case of 'Company X', the case company has a benefit of their market-leader position and being a well-known brand as they hold a leading position when it comes to their respective industry (Company X, 2020). This allows the company to benefit from a strong business position and related benefits such as (financial) resources and many stakeholders (Company X, 2020). According to IDG (2019), the case company is able to benefit from their position as this offers them the option to develop digitalisation practises within the company. When it comes to their sourcing practises, the case company aims to have a high sourcing loyalty, which currently is around 80% (Company X, 2020).

4.3.9. Supplier Readiness

The authors of this study linked the code 'supplier readiness' to the empirical data a total of 8 times. This code refers to the state of being ready or prepared for the adoption of technological tools in the supplier selection process. The automation expert from 'Company X' stated the following:

"The main one is probably that the suppliers are understanding and using it, otherwise it does not make sense and does not bring any value. And of course, for us, we need to understand it as well, from the algorithmic models to really have trust that it actually works" (Interviewee, 2021).

The interviewee (2021) states the importance of suppliers disposing over the ability and willingness to use matching technologies. This is in line with empirical data from the content analysis, which showed that aspiring suppliers need to have certain aspects in line. However, the interviewee (2021) stated that implementing this and streamlining this might be a challenge as the return on investment (ROI) is not fast, meaning that it takes a longer time to profit from the benefit. Moreover, the interviewee mentioned that this is also the reason that makes it difficult to prioritise (Interviewee, 2021).

4.3.10. Industry Standard

The code 'industry standard' was connected to the empirical data 8 times and as the name gives away, relates to the norm in a certain industry. For the case company, this translates to having open dialogues with other companies and industries to discuss what the state of affairs is regarding technological innovation (Interviewee, 2021). The following statement from the interview illustrates this:

''Yes, to a certain level. We meet up with different companies/industries at different forums and sessions and mostly there are very transparent dialogues'' (Interviewee, 2021).

Besides learning about technological standards from competitors, the case company also considers industry standards in terms of environmental sustainability and human rights (Company X, 2020). For example, the case company helps suppliers to improve the working conditions for the employees that work in production. Moreover, 'Company X' does this through their social audits for which they specially focus on suppliers that manage the case company's corporate brand in countries that they deem as high risk in regard to complying with the requirements.

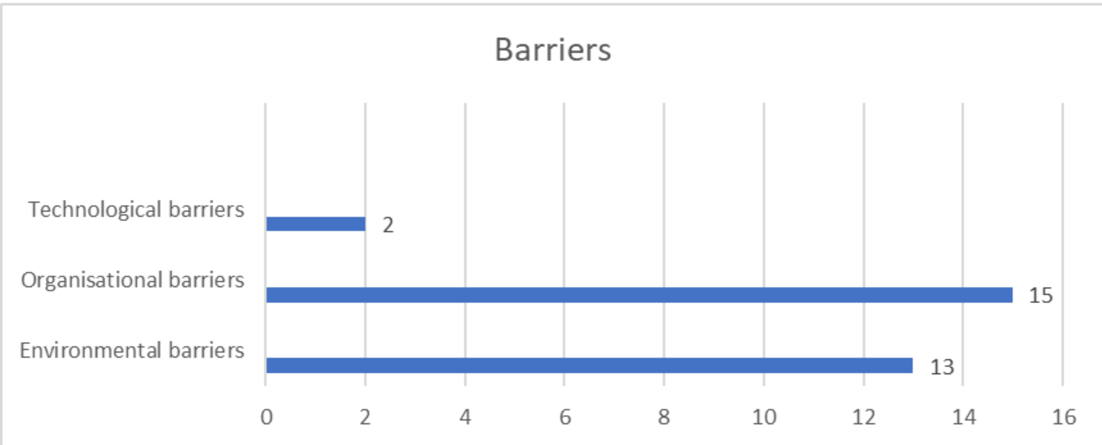
4.3.11. Industry Trends

The last code that the authors assigned to this theme, is the code 'industry trends'. This particular code was linked to the empirical data a total of 8 times and refers to a company's awareness of industry trends. As 'Company X' has a high level of change due to the industry that it is, this awareness is reflected in understanding the importance of being knowledgeable about the effects of the changing market, customer segments and market trends (Company X, 2020). The interviewee (2021) mentioned that staying up to date is a continuous movement and that the company is constantly keeping up with trends (Interviewee, 2021). The case company has the advantage that they are able to benefit from several strong market trends in their industry, such as population growth and a greater focus on personal health. Moreover, 'Company X' is aware of customers demanding more sustainable products and recognise that they need to find a way to combine this with them valuing long term collaboration with their suppliers as the latter is of essence for the progression of the cooperation as well as the stimulation of technological innovation (Company X, 2020). Their annual report also mentioned that they are aware of the rapid technological development and digitalisation and how this affects not only their business, but also their customers (Company X, 2020). In addition, this also influences the purchasing behaviour of their customers, but it also offers new suppliers to take part (Company X, 2020). 'Company X' is aware that all of their supply chain functions are affected by this change, from sourcing to data driven offerings to make it more personalised (Company X, 2020).

4.4. Barriers Context

This section entails the challenges linked to the company's readiness to adopt machine learning which includes some barriers concerning the technological, organisational as well as environmental aspects, and gather 30 statements. This theme contains the smallest number of codes amongst the total of four themes, these codes and their frequency is presented in graph 4 below.

The graph illustrates the trends of the barriers for ML adoption in 'Company X'. In the interview, the authors decided to ask an open question in order to get a comprehensive overview of any possible barriers. However, the response of the interviewee was quite limited. Nevertheless, the authors were able to explore a number of barriers from content analysis of the company documents and videos which turned out to be extremely useful to answer research questions.



Graph 4. Barrier Related Codes and Repeatability

4.4.1. Technological barriers

From a technology perspective, the authors found fewer codes in comparison to the other two contexts and linked 2 codes with the empirical findings. One important notion is inefficient processes: the data analyst needs to maximise the efficiency of the processes in order to take out most value from the use cases which can impact the overall efficiency of the system (Speaker 2, 2019). However, this efficiency is affected by unnecessary checkpoints/process steps that could slow down the processes. For example, the enterprise data warehouse approach is a common exercise with organisations where all of the integration has been built layers by layers with several steps, it will take a long time (Speaker 3, 2019; Speaker 4, 2019). Another barrier related to the data protection issues, particularly the security of data transactions. Any breach in the security of the business or personal data could have a significant negative impact on trust in the case company. As stated in the following statement.

"All X Company subsidiaries have an agreement to work jointly in order to ensure personal data security' (Company X, 2021)

4.4.2. Organisational barriers

Before presenting the findings for this theme it is important to mention that trust in ML is considered as one of the most important factors that can influence an organisation's readiness for technology adoption either positively or negatively. From the organisational perspective, the authors identified the greatest number of codes, namely 15. The case company has different product categories which require a different strategy for each category, therefore, to implement new technology such as ML building of new capabilities and structures is required which must be compatible with the new technology to bring business value. This is closely connected with the organisational structure (section 4.2.5.) and strategic alignment components (section 4.2.2.). Since 'Company X' is a big, complex, and old organisation in terms of structure, this could pose a challenge for the company's readiness to adopt ML.

"Yes, I believe that we are a pretty big one. So, that, normally, takes longer to move and also the structure that we have. We are an old company in regard to structures. However, at a certain level, you become bigger, and you need to create new structures in a way that you cannot run the same speed anymore'' (Interviewee, 2021).

Another barrier addressed by the respondent was the policy issue, meaning that implementing the ML in the supplier selection process is not on the Company X agenda at the moment as well as it also accounts for return of investment, generally companies intend to get a return on investment in a shorter time as possible which explicitly visible from the below argument. In addition, lack of support and commitment from top management could also impact the readiness for technology adoption as illustrated from the below quote.

"I think that it is more regarding our prioritisation. We have other areas that we prioritise. But if you wish to do it, then you probably can go pretty far, even now with the capability that is on the market today. So, I would say that it is more a matter of prioritisation and return of investment of what we do in different areas" (Interviewee, 2021).

The authors noticed a crucial challenge of not having the right place or adequate IT architecture to innovate which is often faced by many organisations. Some of them choose to use the cloud to do innovation. However, the cloud is often not a part of the innovation architecture which leads to legal discussions. In addition, another critical factor found during the interview was the knowledge awareness and technical expertise to understand and apply the ML in the business process. This could also lead to a lack of trust which is a vital element to impact decisions to adopt ML technology. As below quotes represent.

"And of course, for us, we need to understand it as well, from the algorithmic models to have trust that it works. So, also the confidence in the program and these kinds of capabilities from our part" (Interviewee, 2021).

"(…) I think maybe the biggest problem is: do we trust this? And do we think AI is smarter than us? I think here is where the challenge of the transformation comes" (Speaker 1, 2020).

''The focus of the Company X is to have an efficient IT platform for business operations in order to ensure digital trust which is critical for a successful digital transformation'' (Company X, 2020).

At an organisational level, another barrier in adopting new technology is that the innovation is usually carried out in silos, and data is also processed in silos without any communication between different departments whereas communication and collaboration is the key to success. Furthermore, the lack of agility often creates friction and potential architectural rebuild. Which is illustrated in the below argument.

"It is quite common that innovation is often done in a silo. The development and maintenance teams are usually working separately from the innovation team, which creates friction and potential architecture rebuild (...)" (Speaker 4, 2019).

4.4.3. Environmental barriers

The authors brought up the notion of any barrier related to the environment that could impact the technology adoption process and gather 13 codes. Findings show that supplier readiness can be considered as a barrier for technology adoption since the suppliers need to understand and must be able to operate the ML technology in order to produce shared value otherwise this lack of awareness would negatively impact readiness decisions. This was pointed out by the respondent as presented in the statement below.

"*The main one is probably that the suppliers are understanding and using it, otherwise it does not make sense and does not bring any value. And of course, for us, we need to understand it as well, from the algorithmic models to have trust that it works" (Interviewee, 2021).*

Nevertheless, presently applying ML technology in the supplier selection process might take a longer time to get the benefit back. Similarly, the innovation process is deemed as a long process and the implementation of this process often involves long legal and privacy issues which could restrict the adoption of technology. The following statement confirmed this notion.

"It takes a long time to get to the innovation phase. Legal and privacy questions become the subject of long ongoing discussions (…)" (Speaker 4, 2019).

Furthermore, the changing dynamic market conditions can act as a barrier to a company's overall readiness towards digital transformation. For instance, automation, changing consumer patterns, or buying behaviour. In addition, competitor's pressure also plays a key role in strategy making with regards to adopting innovative technology ML.

‘‘Company X has volatile market conditions with a high rate of change since disruptive technologies and fast pace digitalization are impacting consumer behaviour, buying patterns and business trends. These new market trends are transforming the retail industry and also supply chain including sourcing, production, logistics and online sales’’ (Company X, 2020).

The notion of government regulations and laws is a critical factor to the company’s readiness and adoption decision making due to the support provided by the government for the innovation process. Any event of natural disaster could impose a threat and impact the adoption process while making it longer such as the Covid-19 pandemic has posed several challenges for the case company.

“It is required by the companies to be compliant with new laws and regulations such as environmental regulations and so on” (Company X, 2020).

Chapter 5. Discussion

The objective of this chapter is to analyse the data that was presented in the previous chapter (chapter 4) and to compare it to the relevant academic literature that was reviewed. In addition to that, this chapter aims to provide answers to the two research questions that are formulated in the introduction (section 1.3). The answers to the research questions have been extracted from the empirical findings (chapter 4) and have been held against the relevant academic literature (chapter 2). This will be done through the following parts: section 5.1 will focus on technology, section 5.2 on organisation, section 5.3 on environment, and section 5.4 will discuss the barriers. After this is done, the researchers of this study will attempt to answer the research questions in section 5.5.

The empirical findings of this study support the notion that organisational readiness to successfully adopt ML for selecting suppliers is influenced by various internal and external factors. This study's theoretical foundation is built on the TOE framework, an established theory on technological innovation and technology adoption literature to conceptualise ML readiness in the supplier selection process from the following perspectives: technological, organisational, environmental, as well as the potential barriers. This allows the researchers to examine ML readiness factors against the existing academic knowledge on the subject. Therefore, the objective is to present a comprehensive picture of ML readiness based on what the research findings entail in comparison to the existing literature in order to further expand the scope of existing literature.

5.1. Technology

The findings from the empirical study revealed that a company being more knowledgeable on how intelligent solutions, such as machine learning, could help in making working with these tools and overall practises at a company more efficient. As the code 'technological opportunities' was mentioned the most, it is important to the company that they are able to not only their awareness of the changing environment (i.e., data driven society), but also to recognise and create opportunities in order to concretise this into a strategy. The literature confirms the importance of the ability to understand opportunities as this means a better understanding of the potential risks when it comes to using machine learning as a tool (Omurca, 2012). However, the literature review does not cover the risks and downfalls that a company might encounter when wanting to adopt machine learning.

In contrast, the findings showed that the case company does consider the risk of adopting new technological innovation through the usage of test trials. Moreover, this allows the company to make mistakes, learn from them, and not lose a lot of (financial) resources in the process. This allows the company to optimise the tool and ultimately, discover what works best for their particular practises and deliver value to their business. Both the literature review and the empirical findings showed that understanding the opportunities and benefits of intelligent tools helps a company to further increase their competitive edge (Jöhnk, Weißert, & Wyrtki, 2021). This is in line with the empirical findings as this makes it easier for a company to concretise it and incorporate it into their strategy. Consequently, this allows a company to discover whether there is a compatibility between its practises and the intelligent tool as it is able to provide a better understanding of the added benefits and potential risks (Knapp et. al., 2018).

The findings revealed that this code is the second most mentioned code in this context, which is in line with the fact that the case company is aware of the added value that intelligent tools are able to bring along. Especially the way machine learning is able to learn from data and make fairly accurate predictions, depending on the amount of data that it is able to learn from. Moreover, this means that the company is able to use machine learning to replace certain operational and manual tasks to save resources such as time and financial means.

The literature on the supplier selection process and machine learning does not necessarily focus on compatibility, however, it does emphasize the importance of (digital) data availability for it to be more reliable (Agarwal & Jayant, 2020 ; (Wenzel et al., 2019). In fact, the literature review shows that machine learning algorithms possess capabilities that raise accuracy of outcomes and are able to enable a more efficient decision-making process as the algorithms learn from data through recognising patterns (Agarwal & Jayant, 2020 ; Ni, Xiao & Lim, 2020). Meaning that there is an overlap in what has been said in academia and what is focussed on in the industry. Machine learning algorithms learn without a fixed framework and learn through the data that it has been fed, meaning that the intelligent tool is able to become more accurate over time (Agarwal & Jayant, 2020). The empirical findings revealed that machine learning actually might be applicable in the selection of smaller vendors as it could enable the company to make a more efficient selection of the eligible small suppliers for the reason that the case company has a larger number of small suppliers in contrast to the bigger ones (Interviewee, 2021). This is in accordance with the literature as machine learning, specifically, supervised machine learning is able to help the decision-maker with classification and regression when it comes to selecting from a pool of suppliers and making a reliable prediction (Hiri, En-nadi & Chafi, 2019).

Another important aspect to consider that belongs to the technological context and is related to technological opportunity, compatibility, and data availability is the notion of trust and understanding. This was prevalent in both the empirical data and the literature review. The empirical data revealed that whilst companies are aware of the added value that machine learning algorithms are able to bring for the company to increase their competitive advantage, the trust in and understanding of machine learning capabilities are a challenge when it comes to digital transformation within a firm (Jöhnk, Weißert, & Wyrtki 2021). Moreover, the literature shows that machine learning has the ability to make the supplier selection more efficient for the decision-maker, however, the complexity issue of the intelligent tool and algorithm remains. It comes as no surprise that the literature review emphasizes the importance of building knowledge on machine learning as a tool (Pumplun, Tauchert, & Heidt, 2019). Correspondingly, the findings from the empirical study revealed that the company also has a great focus on education when it comes to the embodiment of machine learning and similar tools. In fact, the focus of the training was not only on the tool itself, but also considered responsibilities, such as GDPR compliance.

5.2. Organisation

The second section of this discussion covered the analysis of the identified factors related to the organisational context, in comparison with the academic literature. During the data collection process, the authors have gathered valuable information on the role of the organisational aspect with regards to the company's level of readiness for ML adoption in the supplier selection process. This aspect was assessed both through interviews as well as with supporting information from company documents and videos. Furthermore, this section will present the data collection findings in association with the literature reviewed for this research and it also includes evaluations of the connected factors and their impact on the case company's readiness to adopt machine learning. From an organisational perspective, the findings generated certain distinct ML readiness factors as well as validate the readiness factors linked to the ML adoption from existing literature.

Starting with the most repeated code in this context, namely ‘strategy’, the empirical findings depict the importance of this factor for ML readiness in the retail industry and particularly in the case of a company. Nonetheless, in the academic literature this factor has been discussed in close connection with strategic alignment which ensures that the ML adoption is beneficial and compatible for the organisation as well as ensure strategic relevance to the organisation and support ML initiatives (Jöhnk et al., 2021). As seen in the literature, the increasing interest in ML technologies has forced organisations to re-evaluate their business models and strategies which require automating business processes by emphasizing strategic actions and initiatives (Bienhaus & Haddud, 2018). Moreover, organisations need to coordinate their key business operations to maximise profitability as well as need to build capabilities to carry out digital transformation initiatives (Bienhaus & Haddud, 2018).

The second most repeated code is the code ‘suppliers selection factors’. This component has been widely described in the supplier selection process literature and is considered a crucial element in decision making for selecting suppliers. The literature has proposed that the supplier selection process is based on multiple decision-making criteria approaches and comprises several different criterias such as price, quality, cost, service, and so on (Weber et al., 1991; Ho et al., 2010). However, the authors of this study noted that the case company has no specific predetermined criteria that are given priority as the supplier selection factors are dependent on the product category, however, the interviewee (2021) mentioned the price and delivery reliability as important factors to consider in the selection of suppliers. This notion has also been validated in the literature since Karsak and Dursun (2015) pointed out that it is difficult to identify criteria for the supplier assessment and to take on a specific strategy for selecting suitable suppliers. Surprisingly, the researchers noticed the absence of machine learning applications in the supplier selection process while examining the leading retail case company. Unlike the existing literature where many scholars have applied different ML methods in the supplier selection both individually and in combination with multi-criteria decision-making (MCDM) approaches (Wenzel et al., 2019). Previous literature shows that the ML application exhibits the ability to reduce decision making time to evaluate and analyze the suppliers for reliability which would minimize the risk in the supplier selection process (Hiri, En-nadi & Chafi, 2019). For example, Cavalcante et al., (2019) proposed that the integration of supervised ML algorithms with other traditional MCDM methods can result in improved reliability of suppliers, which is a factor that is deemed important by the case company.

In the findings, another distinct component is observed by the researchers, namely, ‘policy and procedures’ which refers to guidelines that steer decisions. Interestingly, it was discovered that this component is not identified as a separate factor for ML readiness in the literature review. Similarly, findings indicated that the ‘data protection’ component is imperative to ensure company market position as well as to trust in the business activities, while it can be seen that it has not been covered much by the literature review. Though Jöhnk et al., (2021) in a study of organisational AI readiness factors explored the factors of the category data which were deemed necessary for AI-based models, illuminating data availability and data accessibility in order to create AI solutions.

Other factors that were discovered in the empirical findings are ‘organisational structure’ and ‘culture' that are also part of the TOE framework as stated in the beginning of this chapter. The literature on innovative technology revealed that ‘organisational structure’ and ‘culture’ have a deep effect on the adoption process for new technology. The complex organisational structure might hinder the adoption process and discourage the firm's readiness while culture can influence trust and information sharing resulting in enhanced innovativeness and change management (Tran et al., 2011; Jöhnk et al., 2021). Likewise, the empirical findings support the role of these two factors to build a foundation for innovation and continuous learning of new things in order to cope with dynamic changes. This brings up the importance of change management which is another factor identified in the case company. Since 'Company X' is operating in a highly dynamic retail market, it needs to be responsive in order to stay competitive. The case company has already applied ML in several processes however, these disruptive changes need to be managed in a structured way by engaging employees in change management to successfully adopt changes. This also emphasize the importance of on-job training and internal education of employees in order to enhance skill sets and technical expertise. This factor is also mentioned in the empirical findings and reflects that the company is investing in on-job training of data managers and data analysts to ensure system integration.

Lastly, on the basis of the reviewed literature, the authors noticed the importance of resources and top management support for ML readiness, and, correspondingly, are also part of the TOE framework. The findings emphasize the significance of resources by stating it more frequently than top management support which is rarely mentioned. However, it is evident from the response that management support and commitment are highly valued to facilitate readiness for ML applications as Damanpour and Schneider (2006) report that the management can directly decide on the adoption of innovation and distribute resources. AlSheibani et al. (2018) described top management support as a critical factor by arguing that without management support a company is unable to maintain competitive position as well as unable to adopt innovations. According to AlSheibani et al. (2018) human, financial and technology resources and top management support positively influence ML readiness. They further added that the company with more resources has the opportunity to increase their readiness to adopt innovative technologies for example with ample financial resources a company can invest heavily in ML technology (ibid.). The respondent shared the same opinion that the company provides the resources with broader perspective at all levels which is not specific to supplier selection areas such as updating skill sets in terms of technical expertise.

5.3. Environment

For the context of environment, the empirical findings revealed that 'technological infrastructure' is an important factor that is able to make it possible for a company to share data safely and efficiently. This is reflected in the case company's investments, as they have heavily invested in their IT department over the last few years, which is an aspect that the company aimed to have in place in order to enable the development of digitalisation. Moreover, the focus for the case company was to increase the level of data security and improve the digital infrastructure (i.e., system) to increase the level of safety and productivity. Also, the aim of improving the digital infrastructure was to reduce the complexity of managing digital systems for the employees of the case company. In a similar manner, the literature review reveals that prior to investing any technological innovations in an organisation, a company must have a certain level of IT innovation in place as this enables the company to successfully make use of the infrastructure as well as integrate data (Tran, Huang, Liu, & Ekram, 2011). The literature emphasizes the importance of the external environment factors as a crucial part for evaluating a company's readiness to adopt technological innovations such as an intelligent tool like machine learning (AlSheibani et al., 2018). Moreover, the literature review confirms that the management and development of IT infrastructure enables a company to adopt innovative technologies (Tran et al., 2011).

Another important factor is 'certifications and standards'. The findings of the empirical study reveal that this particular code was repeated the most out of all codes in the environmental context. This might imply its importance within the environmental context. The case company mentioned that it requires suppliers to have certain certifications and standards in place for it to be able to work together. This can range from environmental requirements, to ensuring that human rights are not violated. Interestingly, this is not something that is mentioned in the literature of the respective topic. One could argue that this factor is closely linked to the factor 'industry trends and standards', as certain social and environmental issues are only adopted after discovering that their customers value this. The literature specifies the importance of taking into account 'industry requirements and standards', as this allows a company to be up to date of competitors practises and improve their competitive advantage (Pumplun, Tauchert, & Heidt, 2019). Likewise, the findings revealed that to a certain extent, the case company has open dialogues about technological innovation with various companies within different industries. It allows the company to learn from others and have a better understanding of their developments in regard to technological innovation. Then, the empirical data revealed that the case company was able to use industry trends to their advantage and it appeared to be an important factor in the environmental context, the literature does not focus specifically on industry trends, but rather competitive pressure as it reveals that the pressure from competitors motivates companies in similar industries to accelerate the adoption of technological innovations (AlSeibani, et. al., 2018).

Besides certifications and standards, ensuring compliance with 'external policies and frameworks' are important for both the case company itself, as well as for their suppliers. For example, compliance with the GDPR privacy and security law and the guidelines from the OECD for multinational companies (Company X, 2020). The findings reveal that for the case company, the challenge lies in the preparation phase of implementing a new intelligent solution as legal and privacy issues become an important aspect, especially when it comes to data handling, storing, and sharing. As a result of this, the case company manages the details that need to be considered to have it handled, stored, and shared safely, which means that appropriate resources are required to be able to realise this. Similarly, the literature review affirms under the context of the handling data, especially when training their intelligent tools, that this is done in accordance with government privacy and security laws, such as the GDPR law (Pumplun, Tauchert, & Heidt, 2019).

5.4. Barriers

The last section of this chapter concerns the presentation of barriers against the existing literature as well as an evaluation of what might have been discovered in the ML readiness literature. As the previous chapter indicated this section contains fewer quotes, yet it is crucial to assess the readiness for ML adoption in supplier selection. This section will analyze the empirical findings in comparison to the past research reviewed in existing academic literature. The argument will be presented from the three perspectives, namely, technology, organisation, and environment.

From a technology perspective, empirical findings pointed out the challenge of inefficient processes due to multiple layers of data, and unnecessary steps that slow down the processes and reduce the value from use cases which ultimately affect the efficiency of the system. Tran et al., (2011) also reported the absence of standardization of systems as well as compatibility issues which might impact the system efficiency. Findings revealed another barrier to protecting personal data since any breach of data security might hurt the company's market position and can create trust issues. Previous studies also emphasize the importance of data transaction security (Tran et al., 2011). However, it can be seen in the literature that the complexity of machine learning applications often causes data traceability challenges (i.e., black box issue) which make it difficult to achieve transparency (Reim et al., 2020). However, it is surprising to notice that findings did not bring up this challenge. Likewise, the cost of investment for technical solutions is considered a big barrier to adopt ML in the organisation (Tran et al., 2011). Yet, it is not specifically pointed out by the respondent.

The second aspect is the organisational context, which is the most frequently mentioned barrier during the finding. This could mean that barriers that fall under the theme of organisation, should be mitigated in order to increase the level of readiness of ML adoption in the supplier selection process. This theme considers inadequate IT architecture as a barrier in adopting ML technology as presented in the empirical findings, surprisingly, the literature has paid little attention to this topic as a barrier, besides, the use of cloud platforms as an alternative architecture could lead to legal issues. Therefore, this is essential for an organisation to have a proper infrastructure to innovate in order to increase readiness for adopting ML.

Another challenge shared by the interview respondent was not having ML as a priority on the company's agenda which corroborates the challenge of lack of top management leadership and commitment for ML adoption. Tran et al., (2011) and Pumplun et al., (2019) also argued these claims and stated that lack of commitment from top management could impede the readiness for machine learning in the supplier selection process. Furthermore, lacking trust in AI among employees is noted as a major barrier with regards to organisational perspective, Reim et al. (2020) argue that without appropriate knowledge and understanding, people will be less inclined to trust ML applications, therefore trust is deemed critical for innovation acceptance within the organisation. Furthermore, empirical findings described some other important barriers such as complex organisation structure, poor knowledge, and lack of agility since innovation is often done in silos which could create friction. These statements on barriers are explicitly argued in the relevant literature by Tran et al., (2011) and Reim et al. (2020) stating that lack of complex hierarchical structure, poor or lack of system knowledge and technical expertise, and lack of system integration might hinder the successful digital transformation.

Finally, yet importantly, the researchers noted that government regulations, supplier readiness, and competitive pressure are some of the environmental barriers extracted from the findings. These barriers have been reported by scholars such as Tran et al. (2011) and Pumplun et al. (2019) in the existing literature. Nonetheless, the interview respondent highlighted the importance of suppliers' awareness and understanding for ML application in order to enhance the level of ML readiness for the supplier selection process. In addition to this, the empirical findings also shared an interesting view regarding the long process of innovation which could lead to legal and privacy issues making it difficult to decide on ML risks and benefits and ultimately disrupt the ML adoption readiness. Further, competitive pressures, new market trends, and consumer changing purchasing behavior also pose challenges to ML readiness at an organisational level. According to Tran et al., (2011) the absence of consumer demand and without pressures from competitors it is difficult to drive innovation readiness in an organisation. Lastly, it can be seen from the literature review that poor or lack of a national IT policy, an ineffective legal and regulation system, inadequate IT infrastructure, and lack of marketplace are also identified as barriers to adopt machine learning (ibid.)

5.5. Answer to Research Questions

In this final section of chapter 5, the authors of this study will attempt to answer the research questions that were stated in the introduction (chapter 1). This will be done based on the arguments and statements presented in the previous sections above (section 5.1 to 5.4).

5.5.1. RQ1: What factors enable an organisation to facilitate machine learning readiness in the supplier selection process?

The discussion contains an analysis based on the empirical data and the literature review revealed that there are many factors that are able to facilitate a company’s machine learning readiness in the selection of suppliers. In order to connect academic literature to industry practises, the researchers of this study decided to apply the determined factors based on ‘Company X’ in the retail industry in Sweden and the Baltic area. The empirical findings reflect a number of valuable insights from a holistic perspective taking into account the three contexts, namely technology, organisation and environment. The researchers identified factors that can be considered as important for a company’s ML readiness in the supplier selection process. Based on the insights that have been gained, the following factors have been established:

Technology:

- Dispose over a novel understanding and responsive attitude

Organisation:

- Align organisational structure and culture with digital strategy
- Promote internal education and training

Environment

- Compliance with external policies, frameworks, and laws
- Acquire an advanced IT infrastructure
- Attain and preserve competitive edge through receptivity of industry trends and standards

These six factors cover all three contexts and are deemed as most important for a company’s readiness facilitation when it comes to machine learning applications in the supplier selection process. Although, it seems that from all these three contexts, codes related to the organisational context are connected to statements the most, which could imply that this is an important theme for companies to focus on. The objective of this research study was to investigate and identify which factors could influence and facilitate a company’s readiness for the adoption of ML. Thus, the answer to the first research question is that the above identified factors have the ability to facilitate a company's machine learning readiness in the supplier selection.

5.5.2. RQ2: What barriers disrupt a company’s readiness to adopt machine learning in the supplier selection process?

The answer to the second research question is based on the number of barriers identified from both the empirical findings and literature review. Based on the discussion, it becomes evident that a number of barriers might hinder a company’s readiness to adopt machine learning in the supplier selection process. When considering the technology context, data security and lengthy processing time to optimise the reliability for ML applications are seen as a challenge. In addition, important barriers to consider in the organisational context might be the lack of trust in ML capabilities and the lack of ML prioritisation at a strategic and management level. Lastly, from an environmental perspective, important barriers that might interfere with a company’s ML readiness are ineffective government policies, a lack of competitive pressure, supplier preparedness, and incompatible infrastructure.

Chapter 6. Conclusion and Recommendations

This final chapter aims to conclude the study by presenting a summary of the findings and discussion that were presented and discussed in the previous chapters (section 6.1). After the summary has been presented, this will be followed by a concluding discussion (section 6.2) in which both this research study and previous research studies will be discussed. The latter aims to add to the limitations that are relevant to this research paper and will be presented alongside recommendations for future research in this field of study.

6.1. Conclusion

The main objective of this research study was to understand how companies facilitate machine learning readiness in the process of selecting suppliers and to discover what factors are most relevant to facilitate this. The second objective of the study was to understand which barriers might present itself as a hindrance when it comes to determining a company's machine learning readiness in the supplier selection process.

The authors of this study composed two research questions in order to explore the factors and barriers that are connected to machine learning readiness in the supplier selection process. The research questions have been answered by thoroughly reviewing the existing academic literature and was complemented by data that was collected through a single case study which consisted of a company interview and content analysis of company documents and videos. In order to summarise the results of this research study, the authors created figure 6 below to illustrate the established factors that enables a company to facilitate machine learning readiness in the supplier selection process.

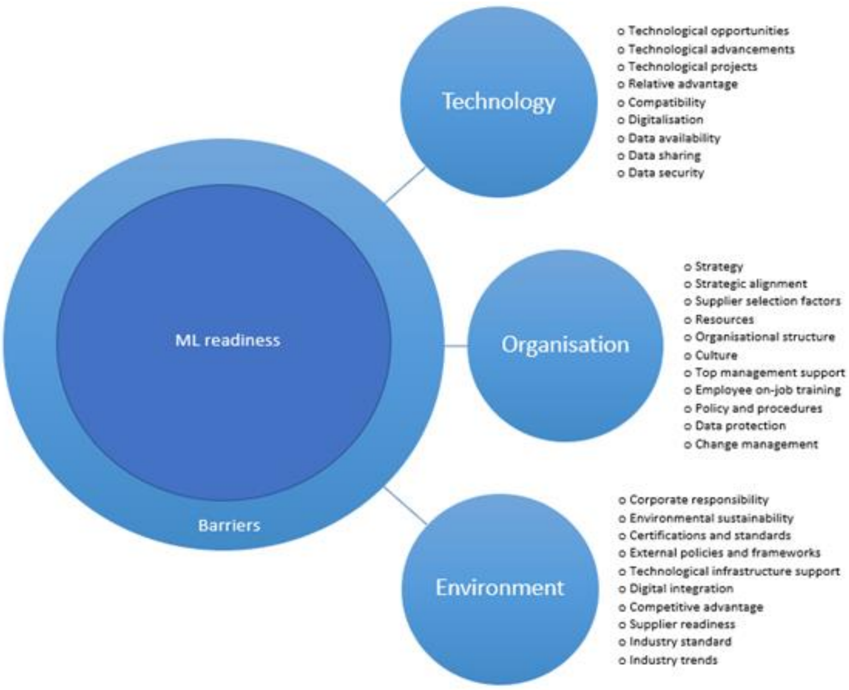


Figure 6. Factors that Facilitate ML Readiness in the SSP

It is important to consider that the above-mentioned themes have related factors that can be viewed from various perspectives. Also, in connection to the three contexts, it is important to be aware of the barriers that might prevail as this might hinder a company's preparedness to adopt ML in the supplier selection process. Moreover, it is important that retail companies consider all three contexts (technology, organisation, and environment) when promoting the adoption of machine learning and take into account the related factors that were established to facilitate ML readiness in the supplier selection process within their company.

The leading retail company was the case that was analysed for this research study. As stated before, the company does not make use of machine learning applications in the supplier selection process. The authors are able to conclude that the case company meets most of the crucial factors and are not only aware of the challenges that they might encounter, but also try to eliminate them through facilitating favourable conditions. As the research process has been able to illustrate, compliance with the established factors in figure 6 can be seen as a way to facilitate readiness to adopt ML technology in the supplier selection process, it is in this way that companies in the retail industry are able to facilitate this. However, it is also important for companies to be aware of challenges, for the reason that they might be an obstacle in the adoption of ML in the selection of suppliers.

6.2. Reflection

In order to deliberate the overall research, the authors dedicate this section to a reflective discussion of the main points that the study has presented in the previous chapters. Moreover, this section aims to highlight the core of this study as well as assess the research contribution.

Firstly, the background information on the case company in the introduction could have been more detailed, however, since the leading retail company wanted to maintain anonymity, this left less room for the authors to mention specific details in both the introduction as well as the rest of the research. In terms of the literature review, the authors rather enjoyed the preliminary research on the topics of facilitating technological readiness at companies, machine learning and the supplier selection process. Despite not including themes within certain topics such as technical methods and applicability of machine learning, it still contributed to the understanding of the topic and scope of this study.

Secondly, the authors believe that due to limited time, the case study could have been deeper if it were able to have been enriched with more interviews at the same company, specifically, in relation to the procurement department. In this way, the authors would have been able to involve various interviewees and enhance the amount of data that was available.

Thirdly, the methods of this study have been altered for the reason that the authors were unable to interview more employees at the case company or at any other company for that matter to turn it into a multiple case study and compare data. Therefore, this led to the current construction in which the authors focus on a single case study.

Lastly, the findings chapter presented the empirical data alongside the process of the study and included statements from the company interview and content analysis of company documents and videos, in which only the relevant quotes were selected and highlighted. Due to limited data access in the form of multiple interviews, this might affect the quality in terms of generalisability. Then, in terms of the discussion chapter, the findings were compared to the relevant academic literature in accordance with the TOE-framework, however, since the literature on this respective topic does not focus on certain topics such as risks and data protection when adopting ML technology in the supplier selection process.

All in all, the main objective of this study was to expand the current literature on the topic of machine learning readiness in the supplier selection process, and specifically, to explore how companies in the retail industry are able to facilitate this phenomena and what factors are important to consider. Also, for these companies, it is important to recognise certain barriers as these might be of hindrance in the facilitation of ML readiness in the supplier selection process. For the specific case company, the practical implications are that the findings and discussion chapters revealed that the case company is ready and willing to adopt ML for all their business operations in due time, and in particular for the selection of suppliers, as there is a rather high compliance rate with the ML readiness factors as well as an understanding of potential challenges that might hinder the company in this process. Moreover, the study aimed to explore the ways companies in the retail industry are able to facilitate ML readiness and highlight which factors are important and which barriers to be mindful of through the study of a thorough single case study. As a matter of fact, the authors amended the TOE framework and re-established factors in the three themes (see figure 6), making the presented study suitable for future researchers that want to gain knowledge through exploratory research.

6.3. Limitations and Future Research

This section of the chapter aims to state the limitations that were encountered during the process of this research study and will conclude with future recommendations. The main limitation that the authors of this study encountered were due to restrictions caused by the current COVID-19 pandemic as it was fairly difficult for the authors to find companies who were willing or able to participate in the study due to a lack of capacity. Nonetheless, the authors were able to find a prominent retail company that was willing to participate as a case study, however, the authors would have preferred to interview more employees to gain a deeper understanding on certain topics such as the supplier selection and procurement at the case company. Since this was not possible, the authors decided to interview people at other companies who are directly responsible for purchasing, sourcing, and relations with suppliers. However, the authors decided that it would be less fitting and therefore, did not include them as it would decrease the level of thoroughness in regard to the single case study. Nonetheless, the authors believe that the efforts to collect more data through interviews did not go to waste in spite of exclusion as this contributed to a deeper understanding and the overall train of thoughts throughout the study.

Another limitation that was connected to the case company, is the fact that they are a market leader in their particular industry in Sweden, which meant that the company was restricted in sharing information when it concerned details of the supplier selection process and automation technologies. In a like manner, the academic literature on readiness in connection to the supplier selection process and machine learning was rather little and on the other hand, the literature of the supplier selection process in connection to automation was rather technical and was left out due to this reason. Moreover, the authors decided to focus on a general description of machine learning as this was more fitting to the scope, as well as to provide the reader with a basic understanding of machine learning and the supplier selection process. Thus, the authors decided to concentrate on concepts and not on technical methods and applicability. The previously mentioned points in combination with the case company wanting to maintain anonymity, meant that the researchers were restricted in providing the reader with details and easily accessible information sources.

Considering the points mentioned above, the authors believe that this study can be used as an exploratory research paper for future research. As the study presents an overview of the readiness factors that are important for the facilitation of ML in the supplier selection process within a leading retail company, the authors believe that further research will be of value for companies in the retail industry. Especially, when future research is able to build on this research which can be done through the usage of quantitative methods or mixed methods for example. Also, the authors believe that it would be interesting to see a similar study with This allows for more statistical measurement and could benefit both academia and the industry.

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Appendix 1. Draft Email Case Company

Dear (*name* or *company name* representative)

I am sending this email on behalf of my fellow student, (author name: interchangeable) and myself, (author name: interchangeable). We are master students at Lund University in Sweden and currently, we are completing our MSc in Service Management with a specialisation in Supply Chain Management.

We are writing our thesis on machine learning readiness in the supplier selection process. In order to connect theory to practice, we would like to conduct research by means of a case study. This means that for our qualitative research, we will use a semi-structured interview (i.e., a set of predetermined questions and room for follow-up questions). We would like to find out more about the supplier selection practises at the company and whether there is a machine learning readiness for the selection of suppliers.

This will map out how (*company name*) identifies, evaluates, selects and contracts its supplier(s). Furthermore, we are also interested in learning more about the prior strategy and decision-making process used during the supplier selection process, what is being done to minimise the risks, how relationship (s) are maintained and promoted, and what the company does to enable technological innovation. There will be a total of 14 questions, with a possibility for follow-up questions to be asked, which means that the interviews will be no longer than an hour. We will of course discuss the results with (*company name*) prior to analysing the answers and eventually, share the results with the company.

In order to achieve this, we would like to interview employee(s) or manager(s) who are responsible for the supplier selection process at (*company name*). The interview(s) will be held in English as our study is given fully in English. Due to the current circumstances, the interview(s) will be conducted through a digital conference platform. A recording will be made solely for the purpose of transcribing the interviews and will be deleted once the thesis is approved (beginning of June).

Hopefully, we have managed to spark your interest. If you would like more information about our thesis or have other related questions, please feel free to contact us in the following ways:

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We look forward to hearing from you.

Kind regards,

(Name: interchangeable)

Appendix 2. Interview Consent Form

Interview Consent Form

Thank you very much for agreeing to participate in this study. This information sheet explains what the study is about and how we would like you to take part in it. The purpose of the study is to gain insight on how your company conducts the supplier selection process and the level of readiness for machine learning, from your perspective as a procurement expert.

In order to elicit your views, we would like you to be interviewed by the researchers involved in the Master study 'Service Management, Supply Chain Management' at Lund University. If you agree to this, the (digital) interview will be audio recorded and further details of how to go about this will be given prior to starting the interview. The information provided by you in the interview will solely be used for research purposes. It will not be used in a manner which would allow identification of your individual responses. Thus, this interview will be anonymous. At the end of the study, anonymised research data will be archived until the researchers have obtained the results for this research paper.

Once again, we would like to thank you for agreeing to take part in this study. If you have any questions about the research at any stage, please do not hesitate to contact us.

• I have read and understood the study information sheet provided.

• I have been given the opportunity to ask questions about the study.

• I understand that taking part in the study will include being interviewed and audio recorded.

• I have been given adequate time to consider my decision and I agree to take part in the study.

• I understand that my personal details such as name and employer address will not be revealed to people outside the project.

• I understand that my words may be quoted in publications, reports, web pages and other research outputs but my name will not be used.

• I understand that I can withdraw from the study at any time, and I will not be asked any questions about why I no longer want to take part in this study.

Participant name and signature: ______________________________________

Date:

Researcher name and signature: _____________________________________

Date:

Appendix 3. Case Study Protocol

Purpose

The purpose of the thesis is to explore which factors constitute a company to be ready to adopt ML in their supplier selection process. This study aims to support professionals from the retail industry that work with the supplier selection process, as well as scholars in academia that are active in the supply chain management and procurement field.

Case Study Questions

The purpose of the case study was to help answer the two research questions of this study.

RQ1: What factors enable an organisation to facilitate machine learning readiness in the supplier selection process?

RQ2: What barriers disrupt a company's readiness to adopt machine learning in the supplier selection process?

Data Collection Plan

The case company that agreed to be part of this study is a retailer in Sweden. The authors had contact with someone from the student relations department and referred the initial email to colleagues. Eventually, the authors spoke to an Automation Expert at the company. The interview was conducted over Microsoft Teams and was approximately 40 minutes as it was cut short due to the fact that the interviewee was called in for another meeting. This meant that the remaining four questions were sent through email. It was a semi-structured interview, which allowed for a more organic dialogue and the opportunity to ask follow-up questions to gain new and interesting insights.

Preparation

In order to conduct a thorough case study, the authors attempted to obtain a good understanding of the problem, by obtaining background knowledge of the respective topics through a literature review as well as a semi-structured interview.

Interview Guide for Case Company Interview

General

1. What is your position at (company name)?
2. Describe your role and responsibilities.
3. Describe the supplier selection process at your company?
    a. Is there a specific strategy connected to this process and what is your vision on it?
    b. Who is responsible for the supplier selection process?

Supplier Selection Process

4. Do you compare suppliers and what they have to offer?

    a. In either case, why?

   b. Specifically, which factors do you consider critical?
   c. How often do you select new suppliers?

5. On what basis do you determine new suppliers?
   a. Are these factors predetermined? If so, by who?
   b. In your opinion, what do you deem as the most important factor?
   c. What is the main objective when selecting a supplier?
   d. Is there a particular procedure for evaluating existing suppliers?
6. Do you believe that the company is ready to implement ML applications for the supplier selection process?
7. In your opinion, what are the opportunities for ML applications in the supplier selection process?
   a. In your opinion, what are the benefits for applying ML applications in the supplier selection process?
   b. Could you describe any potential risks while adopting ML application in the supplier selection process?

TOE-Framework

Technology
8. Are you familiar with any types of technology (for instance machine learning) that could be applied during the supplier selection process (in general)?
   a. What does (company name) use?
   b. How do you perceive machine learning in comparison to other digital technologies?
   c. Do you believe that machine learning would be compatible with your supplier selection strategy?

Organisation
9. In what way is the company providing resources (e.g., financial/human) to enable technological innovation within SSP?
   a. What is the role of the top management in enabling this?
   b. How would you describe the culture at the company towards technological innovation?
   c. Do you believe that the size of the company influences the readiness of adopting technological innovations (such as ML)?
   d. Do you facilitate on-job-training (i.e., for particular a particular skill set, in this case, technical expertise)?

Environment
10. Are you aware of the technologies that are being used in your industry/by our competitors?

   a. If so, in what way does it motivate the company?

11. In what way do government regulations and policies assist in the adoption of machine learning applications in procurement?
12. How does customer demand influence the company in the adoption of machine learning techniques in the supplier selection?
13. Which barriers or challenges do you identify with the adoption of machine learning applications in the supplier selection process in terms of technology, organisation, and environment?
14. Is there anything else that you would like to add?