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Master Thesis

Return policies in the apparel industry

*Survey research on how return policies and practices affect consumer behavior
and apparel retailers' performance*

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Abstract

The objective of this master's thesis was to examine the impact of various incentives on consumers' decision to return products in the Norwegian market, as well as the resulting effects of return decisions on the performance of apparel retailers. The objective of the study was to investigate the factors that influenced consumers' decisions regarding product returns, and to analyze the subsequent effects on the performance and logistical challenges faced by apparel retailers.

From the literature review the concepts of lenient return policy (LP), strict return policy (SP), practices, return decision (RD), performance and satisfaction, the author identified three independent variables and two depended variables to what he expected would influence return decision and if return decision influenced performance. The three independent variables were lenient return policy, strict return policy and practices. The two dependent variables were return decision and performance. Four hypotheses were developed to explain the dependent variable. Data collection for this master thesis was done with a survey where the hypotheses were tested with a path analysis.

The findings from this research show that practices had a positive influence on return decision and return decision had a significant positive impact on performance. The independent variables lenient return policy and strict return policy had a negative impact on return decision.

Based on the findings, the paper discusses that managers should focus on internal integration and improve their logistical operations to be more cost effective and enhance customer satisfaction. This paper also argues this could be achievable by changing the leniency or the strictness of the apparel retailers return policy.

Table of Contents

Acknowledgements	I
Abstract	II
List of tables	V
List of figures	VII
List of abbreviations	VII
1. Introduction	1
1.1. <i>Background</i>	2
1.2. <i>Research question</i>	2
2. Literature review	3
2.1. <i>Return policies</i>	4
2.2. <i>Return practices</i>	5
2.3. <i>Return decision</i>	8
2.4. <i>Repurchase intention</i>	11
2.5. <i>Performance</i>	13
3. Conceptual framework	17
3.1. <i>Hypothesis development</i>	18
4. Research methodology design	20
4.1. <i>Search string</i>	20
4.2. <i>Research strategy</i>	21
4.3. <i>Research Design</i>	21
4.4. <i>Sampling strategy</i>	22
4.5. <i>Survey development</i>	22
4.5.1. <i>Operationalization of Variables</i>	24
4.5.2. <i>Pilot-test</i>	30
4.5.3. <i>Data collection</i>	30
4.5.5. <i>Preparing data for analysis</i>	31
4.6. <i>Quality of research</i>	32
5. Results	33
5.1. <i>Sample characteristics</i>	33
5.2. <i>Skewness and kurtosis</i>	37
5.3. <i>Factor analysis</i>	40
5.3.1. <i>KMO and Bartlett's test</i>	40
5.3.2. <i>Exploratory factor analysis</i>	41
5.3.3. <i>Final exploratory factor analysis</i>	43
5.4. <i>Descriptive statistics -Variables</i>	45
5.5. <i>Cronbach's Alpha</i>	46

5.6.	<i>Multiple regression and path analysis</i>	48
5.6.1.	<i>Multiple regression</i>	48
5.6.2.	<i>Path analysis</i>	50
5.7.	<i>Hypotheses testing</i>	53
5.8.	<i>Satisfaction</i>	53
6.	Discussion	54
6.1.	<i>Theoretical implications</i>	55
6.2.	<i>Managerial implications</i>	60
7.	Conclusion	61
7.1.	<i>Further research and limitations</i>	62
	Reference list	A
	<i>Books</i>	A
	<i>Former papers</i>	A
	<i>Former master thesis</i>	A
	<i>Research Papers</i>	B
	<i>Web pages</i>	H
8.	Appendices	54
8.1.	<i>Appendix 1 – Questionnaire from a former master thesis</i>	54
8.3.	<i>Appendix 2 - Questions in Norwegian</i>	57
8.4.	<i>Appendix 3 – Descriptive Statistics of Variable Items</i>	64
8.4.1.	<i>Lenient return policy</i>	64
8.4.2.	<i>Strict return policy</i>	65
8.4.3.	<i>Practices</i>	67
8.4.4.	<i>RD (Return decision)</i>	68
8.4.5.	<i>Performance</i>	70
8.5.	<i>Appendix 4 - Methodology for multiple regression and path analysis</i>	71

List of tables

Table 1: Questionnaire items for categorizing respondents

Table 2: Questionnaire items for Lenient Return Policy

Table 3: Questionnaire items for Strict return policy

Table 4: Questionnaire items for Practices

Table 5: Questionnaire items for Return decision

Table 6: Questionnaire items for Performance

Table 9: Respondents based on gender

Table 10: Respondents sorted into different age groups

Table 11: Highest finished education

Table 12: Most named apparel retailers

Table 13: Skewness and kurtosis metrics for each variable

Table 14: KMO and Bartlett's Test

Table 15: Exploratory factor analysis with a benchmark of 0.30.

Table 16: Exploratory factor analysis with a benchmark of 0.55.

Table 17: Descriptive statistics for all variables

Table 18: Cronbach's Alpha

Table 19: Average score on buying clothes online based on age group

Table 20: Residuals from *Regression equation (output from RStudio)*

Table 21: Coefficients from *Regression equation (output from RStudio)*

Table 22: Summary of *regression equation (output from RStudio)*

Table 23: Common variable created from computing the mean values of the different items

Table 24: Regressions from path analysis

Table 25: Frequency of consumer satisfaction

Tabell 26: Spørreskjemaelementer for kategorisering av respondenter

Tabell 27: Spørsmål i spørreskjemaet for lempeligere returpolitikk

Tabell 28: Spørsmål i spørreskjemaet for streng returpolitikk

Tabell 29: Spørsmål i spørreskjemaet for praksis

Tabell 30: Spørsmål i spørreskjemaet for vedtak om retur

Tabell 31: Elementer i spørreskjemaet for ytelse

Tabell 32: Kundetilfredshet

Table 33: Frequency of items from the variable Lenient return policy

Table 34: Frequency of items from the variable Strict return policy

Table 35: Frequency of items from the variable Practices

Table 36: Frequency of items from the variable Return decision

Table 37: Frequency of items from the variable Performance

List of figures

Figure 1. Framework

Figure 2: Research model

Figure 3: Histogram based on respondents' gender, where N = 103

Figure 4: Histogram with normal distribution based on age (N =103)

Figure 5: Histogram of highest finished education. (N = 103)

Figure 6: Histogram of respondents answer on item Practices_5

Figure 7: Scree plot

List of abbreviations

CRCs	Centralized return centers
DV	Dependent variable
IR	Internet retailing
IV	Independent variable
LP	Lenient return policy
RCF	Reverse collaboration framework
RD	Return decision
RL	Reverse logistics
RM	Return management
RQ	Research question
SCM	Supply chain management
SP	Strict return policy

1. Introduction

Before the widespread adoption of the internet, the majority of people engaged in shopping activities by visiting brick-and-mortar stores or using postal orders. The rise of the internet caused retailers to transition to a form of commerce commonly referred to as e-commerce, online retailing, or internet retailing (IR). In recent years, there has been a growing focus on e-commerce, specifically internet retailing and logistics, within the apparel industry. E-commerce and internet retailing have changed consumers' shopping habits and the future of the retail industry. Main factors that are driving the change in consumers' shopping habits are smartphones, tablets and retailers' increased investment in digital marketing (Ratchford et al., 2022). "One main advantage the online channel has over the offline channel is lower distribution costs" (Ratchford et al., 2022, p. 157). This benefit stems from the capacity to store products for sale online in a few remote warehouses versus the need to store products for sale offline in several physical stores (Ratchford et al., 2022). Physical stores also have shelf and storage limitations and need to be situated in locations convenient to customers, and they are associated with much higher real estate costs, compared to remote warehouses. E-commerce also allows consumers to overcome geographical boundaries (Ratchford et al., 2022). For instance, the pandemic had a significant impact when everyone was forced to stay at home (Ahsan and Rahman, 2021, p. 159). Physical businesses were shut down for weeks at a time, and in certain nations, citizens were unable to leave their homes.

Products and items like packaging are returned from the market several times along the life cycle. The value of commercial returns has an average of 6% of commercial sales (Krikke et al., 2013). For this reason, there has been a rising focus on how reverse logistics in the apparel industry affect businesses, consumers, and the environment (Frei et al., 2020). To compete with newcomers, companies with more established physical stores are also looking at this potential and investing in omnichannel solutions (Frei et al., 2020). Ordering clothes or other products from home through the internet is not a new phenomenon.

Online commerce is growing, and it doesn't seem like that trend will stop soon. The percentage is still significantly lower than traditional retailing, which accounts for 6.3% of the entire retail sector in Norway (Østebø, 2021). This does not imply that

it is little; in fact, the sum is already very large, amounting to reach several billion Norwegian kroner in 2021.

1.1. Background

This section explains the background of this study. “If there is one lesson managers have learned from the industrial era, it’s that long-term corporate success is inextricably linked to a firm’s ability to satisfy its customers” (Vandermerwe, 1993, p. 47). Before the internet became widely used, apparel retailers’ return policy used to be more restrictive with shorter return windows and stricter return conditions (Abdulla et al., 2019). Over time there has been a shift towards more customer-centric return policies. This is because retailers have recognized the importance of offering flexible return policies to increase customer loyalty and satisfaction.

With the rise of the internet, apparel retailers have started to use the online channel, where they use their stores as decentralized warehouses for sourcing e-commerce. The industry has also noticed that several customers are buying the same apparel in multiple sizes, or styles, only to return them later (Aartun et al., 2019). This creates problems for the physical stores because they often only have a few products in each size. This affects their ability to deliver apparel in that size, both online and in the physical store.

This has also increased the focus on logistics within the apparel industry. Advanced technology has played a key role in shaping the development of retailers’ reverse logistics. For this reason, it seemed appropriate to investigate and attempt to conduct a study in this area. There are many approaches to research designs in this area, both quantitatively and qualitatively, and internet commerce is a relatively new topic.

I believe that it would be helpful to send a survey to consumers that buy apparel products online in the Norwegian market. The answers from the different respondents will help the author to see how they respond towards apparel retailers’ return policy. In this study the author has focused on how online retailers return policies and practices affect consumer behavior in the Norwegian market.

1.2. Research question

Many online retailers still handle returns in an “ad hoc” manner and do not make extensive plans. Many internet retailing firms do not want to take returns into

account in their operations or forecasting since they view them as a headache (Hjort et al., 2019). Product returns is a field that has become increasingly comprehensive and important. Products that are returned are rarely fixed or given new packaging. Since customers can reverse their products, e-commerce has increased the amount of impulsive and compulsive clothing purchases while also making it simpler to reverse them. Because of this, illegitimate “borrowing” and “wardrobing” have gained societal acceptance (Frei et al., 2020). It can be difficult to manage product returns for a variety of reasons, including customer behavioral control, marketing and advertising, purchasing, customer service, supply chain, and logistics (Ramanathan, 2011).

For this reason, the author wants to know more about how customers think about returns. Product returns may cause logistical complexity, inventory levels, reverse logistics efficiency, customer satisfaction and loyalty. For this reason, the author wants to look at how apparel retailers return policy affect consumers behavior in the Norwegian market. Product returns are more common in the apparel sector because they are so dependent on sizes and colors (Gelbrich et al., 2017). In this context, individuals clothing, garments, or attire are referred to as “apparel” (Webster, 2023). Apparel products have comparable qualities, problems, and return causes (Ahsan & Rahman, 2021). The author believes it is in this sector that the lenient return policies are making its biggest impact, something that helped him define the scope of his research question.

To limit myself himself, he has only chosen to look at apparel retailers return policy and how they affect consumer behavior in the Norwegian market. This aided me to define the research question:

RQ: How do return policies and practices affect consumer online shopping behavior and apparel retailers’ performance?

2. Literature review

This section contains a literature review, which was conducted on the topics of: return policies, return practices, return behavior and performance. These topics serve as the foundation for developing a framework. The framework serves as a guide in the process of data collection and analysis.

2.1. Return policies

Return policies are the rules retail companies establish to manage the process where customers return or exchange a defective or unwanted product. “Return policies are seller commitments that assure satisfaction to the buyer”. (Bansal & Muzatko, 2021, p. 56)

Return policies are also tactical decisions that require careful early on, because a well-designed returns policy helps both forward and reverse product flow (Wilson & Goffnett, 2021, p. 649).

Return policies can be classified into the following types: lenient, moderate, and strict (Ahsan & Rahman, 2021, p. 149).

Ahsan and Rahman (2021) did a systematic literature review of e-tail product returns research. In their literature review the authors found three types of return policies, where lenient return policies are most researched. In their review, the authors found that a lenient return policy promises to manage product returns in a straightforward manner by providing free reshipment or by imposing generous time limits on product returns.

[A] lenient return policy conveys a positive message to the customer before they make any purchasing decision, it can be considered a form of quality assurance or signal of the high quality of a product and thus offer peace of mind to the customer before they purchase. (Ahsan & Rahman, 2021, p. 149)

Lenient return policies help e-tailers to build customer trust and market reputation, but also to attract more customers which helps to add greater value to their business (Ahsan & Rahman, 2021, p. 149).

Bansal and Muzatko (2021) studied the role of shipping and return shipping prices on consumer intentions to purchase goods in the e-commerce market. They found that a lenient return policy helps to lower return shipping prices and assures that unsatisfied customers can cheaply return defective goods due to dissatisfaction (Bansal & Muzatko, 2021, p. 57).

Emmelie Gustafsson, Patrick Jonsson and Jan Holmström investigated how fit uncertainty impacts product return costs in online retailing, and how digital product fitting can reduce fit uncertainty. One of their findings is that lenient return policies

can encourage customers to overorder and return, where customers order multiple products in different variants, with the intention of returning the least-fitting variant (Gustafsson et al., 2021, p. 879). This increases product returns and product return costs.

Lenient return policies encourage irrational ordering and increase return rates, which has massive implications on consumer behavior and management of the increasingly complicated ecological and financial issue of online returns (Saarijärvi et al., 2017, p. 284).

In Ahsan and Rahman's literature review, the authors found that moderate returns policy is beneficial for both e-tailers and customers. The moderate returns policy is an optimal point restrictiveness and leniency, where it positively enables consumer purchases and firm performance (Ahsan & Rahman, 2021, p. 150).

Ahsan and Rahman found that there has been least research on strict return policies. A strict returns policy involves many gatekeeping rules and restrictions. "Because of customer abuse of lenient returns policies and because of the high costs of returns handling, retailers are in favour of stricter returns policies". (Ahsan & Rahman, 2021, p. 150)

2.2. Return practices

A company's return policy does not only affect their daily activities, but also consumers behavior and their logistics. When consumers are returning their apparel due to misfit, defectiveness, or dissatisfaction, the product will go back to the warehouse or manufacturer. This is known as reverse logistics. "[Reverse logistics is] a process in which a manufacturer systematically accepts previously shipped products or parts from the point for consumption for possibly recycling, remanufacturing, or disposal". (Cricelli, et al., 2021, p. 1)

Livio Cricelli, Marco Greco and Michele Grimaldi (2021) explored the impact of collaboration with customers, suppliers, competitors, research institutions and the collaboration on a firm's reverse logistics innovation. Companies that want to innovate their logistics by re-designing their processes need to collaborate with supply chain partners and non-industry partners. Collaboration in reverse logistics will increase predictability, market knowledge, margins, and a company's mastery of reverse logistics processes (Cricelli et al., 2021, p. 1).

The authors found that horizontal collaboration, vertical collaboration, and collaboration with research institutions increases the likelihood of introducing reverse logistics innovation in a company (Cricelli et al., 2021).

The authors explain horizontal collaboration as cooperation between two or more companies that are at the same level in the supply chain. A company always compares its strategies and practices with those of the best competitors, treating them as benchmarks (Cricelli et al., 2021). Active collaboration between wholesalers, distributors or logistic partners can set standards and accelerate the implementation of reverse logistics (Cricelli et al., 2021, p. 3).

Vertical collaboration includes cooperation with customers and suppliers. Pressure from customers and suppliers has an effect on companies that can bring them to introduce more environmental innovations in general and to implement reverse logistics (Cricelli et al., 2021, p. 3).

Collaboration with suppliers is one of several key facilitators in managing reverse logistics. A collaborative re-design of packaging in a reverse logistics perspective can bring mutual benefits to the manufacturer and the supplier. When suppliers participate in re-designing the packaging, it can reduce the material and recover products, which customers can buy as service parts (Cricelli et al., 2021, p. 3).

Frei, Jack, and Brown (2020) used a multi-case study approach where they looked at return processes, identified vulnerabilities, and developed a returns cost calculator. A returns cost calculator is designed to help companies to compute the financial impact of product returns. It is very challenging for retailers to handle product returns in several states. Rarely are returned products repaired or given new packaging. E-commerce has increased compulsive and impulsive clothing purchases while also making it simpler for consumers to return them (Frei et al., 2020). This increases transportation and product waste, which leads to harmful effects on the environment (Frei et al., 2020, p. 1616).

The authors recommend companies to treat returns as an asset instead of a cost. This means that most retailers look at returns as an object that increases their cost, and not as an opportunity for improving their financial results. Some retailers have started to use existing policies where they are being less lenient with returns, while companies like ASOS and Amazon have started to blacklist serial returners who do not keep enough of the ordered products (Frei et al., 2020, p. 1616).

The authors found that product return processes are usually complicated and prone to both internal and external fraud, where they are inefficient and lack sustainability. They can generate big losses to the business, since returns data are often not systematically collected, monitored, or reported to the management (Frei et al., 2020, p. 1613). For this reason, the authors believe that retailers, manufacturers, and logistic providers could benefit from receiving guidance on how to implement Lean concepts in product return systems (Frei et al., 2020, p. 1620).

Klas Hjort, Daniel Hellström, Stefan Karlsson and Pejvak Oghazi (2019) used a multi-case study approach which involved twelve e-commerce firms and four logistic service providers. They used an integrative data collection approach, where they conducted semi-structured interviews, documentation, and observations to gain managerial and operational descriptions of returns management processes (Hjort et al., 2019, p. 767).

For many internet retailing firms, consumer returns are regarded as a strategic part of the business, as they are associated with high costs and a steady rise of return volumes (Hjort et al., 2019, p. 770). In returns management processes, where the capacity of information systems is seen as a major barrier, poor internal and external integrations are significant cost drivers. A big challenge in internet retailing is the reverse flow of products. For this reason, it is important to have good RM processes. “Still, many IR firms consider managing returns and reverse logistics (RL) a headache or unimportant”. (Hjort et al., 2019, p. 768)

For the design and implementation of returns management to be done correctly, it is crucial to define the goals and strategy, as well as the function that returns play for the many stakeholders. “RM is a SCM process that implements four activities: returns, gatekeeping, avoidance and RL”. (Hjort et al., 2019, p. 768)

Gatekeeping has made it possible for retailers to interact with the returnee and set standard procedures to prevent unwanted returns, which reduces the need for transportation and warehouse work. The return rates decide the type of gatekeeping that is used. While businesses with high return rates can only gatekeep downstream, and if they have gatekeeping upstream to warehouses or CRCs, low return rates allow the internet to gatekeep downstream.

The authors found that the understanding of returns, avoidance, gatekeeping, and RL is not sufficient to describe how RM is practiced. It was also found that internet

retailing firms design RM to include service as a fifth activity, but they are not properly designed (Hjort et al., 2019, p. 786).

Ardeshilijarimi and Azadivar created a model in their paper for forward/reverse supply chain to satisfy fixed demand with a combination of new and remanufactured products. They found that the percentages of products that are returned can range up to 35% for high-fashion apparel (Ardeshilijarimi & Azadivar, 2014, p. 1767).

2.3. Return decision

The return policy of a business impacts not just its everyday operations but also consumer behavior when it comes to returns of goods.

Zhi Pei and Audesh Paswan (2018) studied consumers online return behavior, where they differentiated between legitimate return behaviors and opportunistic return behaviors. “Legitimate return behaviors are those return behaviors that are acceptable in a mature market, including returns due to product defects, sellers’ fault, buyers’ remorse, or a changed external market”. (Pei & Paswan, 2018, p. 304)

Opportunistic return behavior can be defined as self-interest seeking with guile. Guile means using a cunning or a dishonest method to achieve something (Pei & Paswan, 2018, p. 304).

Pei and Paswan found in their research that customers who are more impulsive are also more likely to return the purchased product, since they buy goods on the spur-of-the moment, which makes them more likely to change their mind after the purchase (Pei & Paswan, 2018, p. 314). Customers who value a product for its uniqueness are less likely to return it since they are picky about their purchases. They are less likely to return the product once they get the item they desire and as long as it satisfies their needs (Pei & Paswan, 2018, p. 314).

Katja Gelbrich, Jana Gäthke and Alexander Hübner presented a pilot study where they introduced a keep reward as a promotion strategy to improve conventional lenient policy (Gelbrich et al., 2017, p. 853). In contrast to the conventional lenient policy, the authors developed and investigated the reinforcing effect of a keep reward on customers' keep decisions. According to the findings of their study, a keep reward is practicable in online shopping, particularly in the low- to mid-price segment when rewards are connected to further purchases. They also conducted two

experimental studies where they verify the positive effect of a keep reward. In study 1 they compared a keep intention compared to a conventional lenient policy. In Study 2, the authors of this article examine whether the frequency of online shopping should be a factor in the choice to maintain a product that is associated with an incentive for further purchases.

Study 1

According to the findings of Study 1, respondents in this study are more likely to keep the product under a lenient policy plus a keep reward than they are under a conventional lenient policy. This is because online retailers give a positive outcome by including a keep reward that strengthens consumers' retention intentions by providing the customers with free shipping on their next order.

Study 2

The closer a customer is to reaching their goal where they can regain the reward with the following purchase, the more likely they are to keep the product(s) they have ordered (Gelbrich et al., 2017).

It is proposed that frequent online shoppers feel somewhat near to this objective. This is because they frequently buy the focal product category, and as a result, they anticipate making a similar purchase in the near future (Gelbrich et al., 2017, p. 859).

Low frequency online shoppers rarely purchase products online. Since they do not frequently buy products, these customers should not profit much from a keep reward. Infrequent shoppers shouldn't find any need to engage in retain activity because the reward is highly improbable for them. Because of this, customers are less likely to repurchase from the retailer that gives them a keep reward, and as a result, they respond more favorably to a lenient policy without the keep reward (Gelbrich et al., 2017, p. 860).

The article written by Kaushik, Kumar, Gupta, and Dixit (2020) studies and prioritizes the factors that motivate returns.

The authors begin with discussing the significance of online apparel returns in the e-commerce business, which may have a huge impact on consumer happiness and loyalty. The authors also propose a methodology for assessing factors that drive

returns from buying apparel online, prioritizing these criteria based on their relevance to customers using the Best-Worst Method (Kaushik et al., 2020).

The researchers discovered that accurate product descriptions, product quality, and the convenience of the return procedure were the most critical factors affecting returns. Additional critical aspects included the availability of customer service, the retailer's reputation, and the availability of product reviews.

The researchers suggest that by emphasizing these elements in their online retail operations, apparel companies may increase consumer happiness and lower the percentage of returns. Apparel retailers will most likely build consumer loyalty and improve their bottom line by concentrating on product quality, clear product descriptions, and a simple return process.

The authors conclude that retailers can improve customer satisfaction and reduce the rate of returns by prioritizing these factors in their online retail operations. Retailers can build consumer loyalty and improve their bottom line by concentrating on product quality, clear product descriptions, and a simple return process (Kaushik et al., 2020).

Gäthke, Gelbrich, and Chen (2022) studied the impact of national institutional environments on e-tailers' return policies and how these policies can be used to manage product returns.

They begin their paper with discussing the importance of product returns for e-tailers as well as the challenges they encounter in handling returns across various national institutional settings. The researchers present a theoretical framework that connects service strategy, institutional theory, and consumer behavior in order to explain the factors influencing e-tailers' return policies and the impact of these policies on customer satisfaction (Gäthke et al., 2022).

The researchers conducted a cross-national study of e-tailers in China and Germany to test their theoretical framework. The authors collected information on the return policies of e-tailers, consumer satisfaction, and the institutional climate in each nation. The authors discovered that return policies in China and Germany vary significantly, since German e-tailers have more lenient return policies than their Chinese counterparts (Gäthke et al., 2022).

Gäthke, Gelbrich and Chen discovered that the institutional environment played a significant role in shaping e-tailers' return policies. In Germany, where institutional pressures for customer protection were stronger, e-tailers offered more generous return policies to legitimize their business practices. In contrast, in China, where institutional pressures for cost control were stronger, e-tailers offered more restrictive return policies (Gäthke et al., 2022).

The authors of this paper conclude that both consumer behavior and the institutional context have an impact on e-tailers' return policies. E-tailers can implement return policies to handle product returns and improve customer satisfaction, and the rules they implement must be customized to the institutional framework in which they operate. Gäthke, Gelbrich and Chen also advise e-tailers to keep an eye on the institutional context in which they operate and consequently change their return policies in order to remain competitive in the market.

2.4. Repurchase intention

The concept of repurchase intention constitutes a fundamental aspect of consumer behavior, particularly focusing on the inclination of a customer to make repeated purchases of goods or services from a particular company. This tendency is strongly influenced by the customer's prior purchasing interactions with the same company (Ali & Bhasin, 2019, p. 147; Hellier et al., 2003). The significance of the repurchase intention has been highlighted in numerous studies, emphasizing the role it plays in customer retention and organizational growth, especially in the expanding landscape of e-commerce (Chaudhuri & Holbrook, 2001; Hsiao, 2009).

In an informative and meticulously conducted study, researchers Asif Ali and Jaya Bhasin developed a comprehensive research instrument that combined a range of variables that were derived from an extensive review of the existing literature within the e-commerce field. The tool was carefully constructed to ensure an accurate representation of each variable, thereby ensuring the validity and reliability of the measurements. In this context, Ali and Bhasin adopted a 7-point Likert's scale to measure the responses, using five items to measure repurchase intention. They further incorporated four items each for assessing delivery quality, perceived price, and perceived value. Given the substantial role of customer satisfaction in influencing repurchase intention, six items were employed to measure this aspect,

underlining the crucial role customer satisfaction plays in fostering repurchase behavior (Ali & Bhasin, 2019; Oliver, 1980; Yi & Gong, 2013).

The researchers focused on online shoppers, which is a rapidly growing demographic that is shaping the face of global retail. They reached out to their target audience via various digital communication platforms such as email and social media outlets like Facebook and WhatsApp, reflecting the increasing use of these platforms for research data collection. Over a span of ten weeks, they gathered their sample data from a distinct group consisting of postgraduate students and lecturers. The primary objective of their ambitious study was to unearth the hidden mechanisms and driving factors that influence consumer repurchase intention in the digital sphere, an area which despite its relevance in the current times, remains under-researched (Ali & Bhasin, 2019).

One of the most compelling findings of their study was the significant influence that perceived price and delivery quality exerted on perceived value. Additionally, they discovered that perceived value heavily influenced consumers' repurchase intention, a result that adds depth to our understanding of the e-commerce consumer psyche (Ali & Bhasin, 2019, p. 153; Zeithaml, 1988). A counterintuitive relationship was observed between the perceived price and the perceived value, with the relationship being negative, a finding that presents an interesting paradox in the realm of e-commerce consumer behavior.

The study conducted by Ali and Bhasin, which contributes to the field, is not without limitations. The data collected was largely from Indian universities, which represents a considerable bias, excluding a significant section of global online consumers. Furthermore, the participants of the study were limited to those with prior online shopping experience, possibly skewing the outcomes in a specific direction. The study did not consider the aspect of trust, which is an integral element in online shopping behavior. This can be potentially attributed to the peculiar characteristics of the Indian online shopping landscape where most online purchases are made from a limited number of trusted retailers (Gefen et al., 2003). The cultural context of the participants, given the geographical confinement of the study to India, could also have exerted a significant influence on the study's findings, calling for a cautious interpretation and application of the findings (Ali & Bhasin, 2019, p. 154).

The culmination of their study yielded significant insights into customer behavior, notably that customers are likely to attribute high perceived value to purchases made from retailers that provide superior delivery quality. Thus, understanding the mathematics of customer perceived value becomes imperative for online retailers looking to improve customer retention and enhance repurchase intention (Ali & Bhasin, 2019, p. 154; Bolton et al., 2000).

In the rapidly evolving world of e-commerce, characterized by relentless competition and short-term customer loyalty, studies like the one conducted by Ali and Bhasin offer invaluable insights to online businesses. Such research can inform strategies aimed at enhancing customer retention and encouraging repurchase intention. Future research in this domain should consider including a more diverse and representative sample from various geographical locations and encompass additional factors like trust for a more holistic understanding of online consumer behavior (Y. Kim & Peterson, 2017; Lee & Turban, 2001).

2.5. Performance

Customers that buy apparel online face a disadvantage compared to customers that buy apparel in a brick-and-mortar store, since they cannot physically try it on, and this creates fit uncertainty. It is crucial to determine whether digital product fitting can lower fit uncertainty and whether it has an impact on the expenses of the retail supply chain.

Using a mixed-method approach, Emmelie Gustafsson, Patrik Jonsson, and Jan Holmström (2021) looked at how fit uncertainty affects product return costs in online commerce and how pre-sales fitting technologies can reduce fit uncertainty. They conducted a case study in the first step to examine how fit uncertainty impacts the businesses' current e-commerce operations. In the subsequent phase, they examined the potential for a computerized product fitting system already in use to reduce fit uncertainty. They accomplished this by choosing sixteen different pairs of shoes from the store. The costs of fitting-related product returns were recalculated in the third step (Gustafsson et al., 2021).

They collected data through interviews, observing the product flow from the point of receipt to reshelving by visiting the retailer's warehouse (Gustafsson et al., 2021, p. 881). The authors tested how a scanner presented a list of best fitting shoes by scanning customers that were included in the test. Costs generated by product

returns, tied up capital, product handling costs, transportation costs, inventory holding costs and order-picking costs were also tested (Gustafsson et al., 2021).

In their study, they found that the cost of return is around 17% of the prime cost where the major cost elements are transportation costs and product handling costs. These two costs stand approximately for 72% of the total costs. The main reason for returns is because of poor fit, which accounted for 55% of the returns (Gustafsson et al., 2021, p. 886). The authors found that test customers would have kept the shoes in 10 out of 38 cases, around 25% of the time. If the scanner would have been better calibrated for fashion shoes like ballerina flats, pumps, and heels, and also given recommendations based on the participants alternative tests. The authors found that if the sensor was better calibrated it could cut fit-related return costs by 80% (Gustafsson et al., 2021).

Klas Hjort and Björn Lantz empirically analyzed and described the effects of return policies on consumer behavior and the moderating effects of the policies on profitability (Hjort & Lantz, 2016, p. 4980). The method involved analyzing transactional data of a Swedish online fashion retailer.

A marketing incentive to attract and maintain repeat and loyal customers can be created with lenient return policies to increase sales. The correlation between maximizing profitability and increasing sales does not exist, because profit is always a company's first priority (Hjort & Lantz, 2016, p. 4981).

The findings of this study demonstrated that repeat customers make a much higher contribution per order when a lenient returns policy is in place, whereas consumers who receive free returns produce a significantly smaller contribution per order. Loyal and repeated customers create a much higher total contribution than customers who enjoy free returns. Lenient return policies do not always benefit the retailer in a long-term perspective, and for this reason managers should customize their return policies according to their customer segments (Hjort & Lantz, 2016).

Kumaraguru Mahadevan (2019) carried out a framework known as the reverse collaboration framework (RCF) to provide supply chain visibility and information sharing to practitioners in reverse logistics collaboration. He used a combination of concept mapping and a deductive approach to develop a reverse collaboration framework, where he connects systems, tools, techniques, and reverse logistics processes.

RL are driven by factors such as extended producer responsibility, environmental legislation, economics, and improved customer service (Mahadevan, 2019, p. 486). Cooperation is the key to success in supply chains and can be a way to decrease costs and make reverse supply chains economically attractive (Mahadevan, 2019, p. 487). “The RL strategy is of critical importance in managing the reverse direction in SCs from consumer to producer”. (Mahadevan, 2019, p. 488)

Return rates of products are challenging to predict and for this reason reverse logistics is needed to set return policies and procedures, where they are being integrated with forward logistics operations when needed (Mahadevan, 2019, p. 488).

Mahadevan’s study shows that by integrating systems, tools, and techniques with reverse logistics processes besides of the reverse collaboration framework will increase performance and productivity of RL processes (Mahadevan, 2019, p. 482).

Edlira Shehu, Dominik Papies, and Scott A. Neslin investigated the effects of free shipping on purchases, customer return behaviors, and total profit. The relationship between free shipping and return rates was something they wanted to research. Free delivery was found to enhance both sales and return rates. The effects of the rise in sales were canceled out by return processing costs and lost shipping earnings, leaving a negative profit impact (Shehu et al., 2020). Additionally, they discovered that it only greatly improved sales for riskier products (apparel), not for less dangerous products (electronics). Brands are no different. It did not increase sales for unknown brands, but it did increase the return rates for the same products (Shehu et al., 2020).

In Matthew Wilson and Sean Goffnett’s research, the authors identified tactical, strategic and operational considerations that are needed to design reverse logistics programs where they also offer industry examples. The authors found key takeaways across a range of reverse logistics activities. The outline strategies managers can use to implement best practices in reverse logistics that not only benefit the environment but also create value for stakeholders and society, enhance and improve customer service and loyalty, and increase market share and revenue capabilities (Wilson & Goffnet, 2022, p. 643).

Li, Wei, and Cai's study "Optimal pricing and order policies with B2B product returns for fashion items" investigates optimum pricing and order policies for fashion products in a B2B context with product returns.

The authors start their paper by investigating the challenges that fashion product producers face in a B2B market, such as demand unpredictability and the impact of product returns on profitability. They then propose a mathematical model that enables producers to calculate the best price and ordering strategies for their items while accounting for the cost of product returns.

The authors discovered that optimal pricing and order policies are affected by a variety of factors, including production costs, product return costs, and the amount of demand uncertainty. They also discovered that manufacturers may increase their profitability by using a variety of techniques, such as giving bulk order discounts, charging a higher price for items that are more likely to be returned, and establishing a more liberal return policy.

The authors conclude that fashion product makers can benefit from taking product returns into account when determining pricing and order processes. Manufacturers may increase their profitability and lessen the impact of product returns on their business by doing so. More study, according to the authors, is needed to better understand the impact of product returns on the fashion sector and to develop more effective return management systems.

Guo, Choi, and Shen (2019) investigated green product development in the fashion apparel industry, concentrating on the influence of competition on firm decision-making processes.

The authors begin by analyzing the significance of green product development in the fashion sector, which has been criticized for its environmental effect. The researchers then provide a model that enables businesses to calculate the best level of investment in green product development while accounting for the impact of competition.

They discovered that the ideal degree of investment in green product development is determined by a variety of factors such as the level of competition, the cost of developing green products, and market demand for sustainable products. They also observed that firms may benefit from investing in green product development even

in a competitive market since customers are increasingly willing to pay a premium for sustainable products.

The authors conclude that, even in a competitive market, green product creation is a realistic approach for fashion companies. Firms may differentiate themselves from competitors and fulfill the rising demand for eco-friendly products by investing in sustainable products. The authors argue that it is required to better understand the influence of green product development on the fashion industry and to develop more effective ways for promoting sustainability in the sector.

3. Conceptual framework

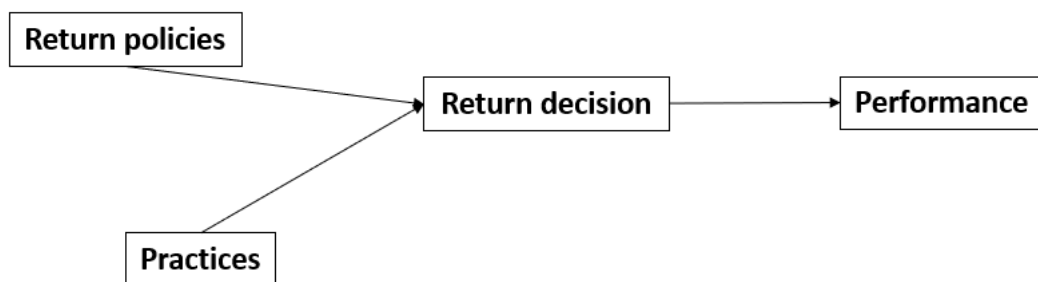


Figure 1. Framework

The findings in the literature have shown that the author's research question is highly relevant and very interesting. The first concept that was explored was apparel retailers return policies. Return policies are rules which are set by retailers to manage the process of handling returns or exchange from consumers (Bansal & Muzatko, 2021). Return policies are tactical considerations that must be carefully considered early on, since a well-designed returns policy aids both forward and reverse product flow (Wilson & Goffnett, 2022).

From the literature review, the author knew that it is very challenging and time consuming for retailers to handle product returns in several states. Return practices could influence apparel retailers' ability to preserve customer satisfaction, loyalty, and perhaps drive repurchasing behavior. This also affects their costs and revenue. Retailers practices of varying return policies over time and across product categories may lead to unrealistic consumer expectations of return control and future reaction (Dailey & Ülkü, 2018, p. 207). For this reason, it seems plausible that apparel retailers practice can affect consumers return decision.

The literature review highlights the potential influence of various factors on the return decisions of consumers when it comes to online purchases of apparel products. The factors mentioned above encompass the return policy of the retailer, comprehensive product descriptions, the accessibility of customer service, the standing of the retailer, and the existence of product evaluations.

The significance of online performance is especially crucial for apparel retailers. E-commerce presents distinctive obstacles for consumers during the shopping process. The inability to conduct a physical inspection, trial, or comprehensive evaluation of the product places the individual at a disadvantage. As a result, comprehensive product descriptions have become a critical component in the effective management of consumer returns, the optimization of reverse logistics, and the reduction of environmental consequences. For this reason, performance is variable that can be affected from consumers return decision.

3.1. Hypothesis development

Practicing a **lenient return policy** can result in a significant number of returns, complicating the reverse logistics process even more. More returns mean more things to check, classify, and maybe repair, clean, or refill, or dispose of, if they can't be resold. Furthermore, the unpredictability of when and how many things will be returned makes handling returned inventory and projecting inventory levels difficult (Hjort et al., 2019), (Frei et al., 2020) and (Cricelli et al., 2021). For this reason, I believe that such a policy could have an impact on consumers' return decision. This variable could also be looked at as an economic incentive because it could influence consumers' decision-making when it comes to returns. For this reason, I propose the following hypothesis:

H1: *A lenient return policy has a positive influence on consumers' return decision.*

A **strict return policy** is the opposite of a lenient return policy, and it can force retailers to underorder, lead to fewer returns and involves many gatekeeping rules and restrictions, because consumers abuse the lenient return policy. For this reason, it seems appropriate that strict return policy could impact consumers return decision. Apparel retailers that practice such a policy can also include many restrictions and gatekeeping rules to avoid returns (Ahsan & Rahman, 2021). This

variable could also be viewed as an economic incentive since it could influence customers' decision-making. Therefore, I propose the following hypothesis:

H2: *Strict return policy has a positive impact on consumers' return decision.*

Practices for apparel retailers can be referred to operational procedures, protocols, or systems that retailers use to effectively manage their business. These practices include a wide range of components of the retail industry and are crucial to accomplishing strategic goals such as improving customer happiness, boosting profitability, and encouraging sustainability. Therefore, this variable could be viewed as an economic incentive since it could influence consumers' return decision. For this reason, I propose the following hypothesis:

H3: *Practices has a positive impact on consumers' return decision.*

Return decisions are the decisions that customers make about whether to return a product that they have purchased. Consumers' return decisions is most likely being impacted by apparel retailers return policy and practices. There it seems like consumers return decisions can affect apparel retailers' **performance**. For this reason, I have proposed the following hypothesis:

H4: *Consumers return decision has a positive impact on apparel retailers' performance.*

The author created the research model, which is shown in in figure 2 below.

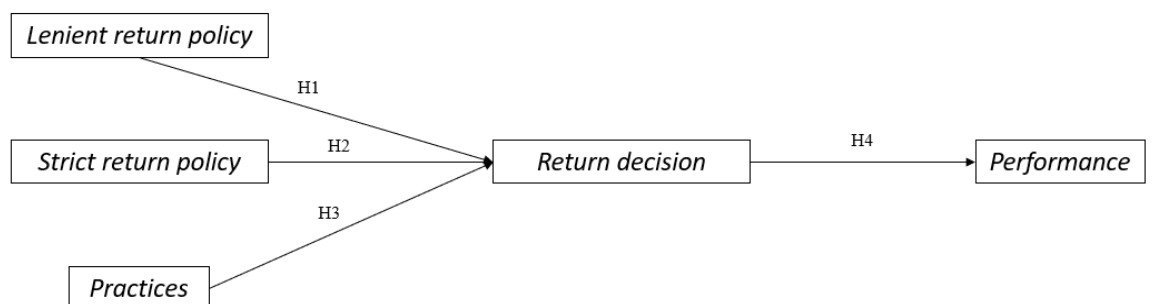


Figure 2: Research model

This figure shows the three independent variables on the left side, while the two dependent variables are shown on the right side in figure 2. The research model above has been used for data collection and analysis.

4. Research methodology design

In this section I will describe all the methodological choices used in my master thesis. Firstly, I am going to present the research strategy and the research design. Secondly, I will discuss sampling strategy and the sampling method. Thirdly, I will discuss the survey development and the pilot-study processes. Further in this part I will explain the process of data collection and data collection. Finally, I intend to explain how the quality of my research has been secure throughout the study.

4.1. Search string

To find relevant research articles I conducted a limited literature review when finding the research and defined a search string:

(“product return” OR “commercial return” OR “consumer return*”) AND (“e-commerce” OR “online shopping” OR “electronic commerce*”) AND (“reverse logistics” OR “reverse collaboration*”)*

To find relevant research articles, the author used several different platforms such as Web of Science, ScienceDirect, SpringerLink, Wiley and Emerald insight. The search string gave me 24 articles when I used the Web of Science platform, which I screened by title, where I also read the abstract and went deeper into the articles, I felt were relevant for my research. When I entered the same search string in the Science Direct platform, I got 1 065 987 articles sorted by relevance. In this platform I chose to limit the timeframe from 1980 to 2023, since they seemed most relevant, and I also screened them by title and found articles that I felt are relevant. They were also for review- and research articles in the platform. When I used my search string in SpringerLink and refined the search to articles and subdiscipline to Business and Management, I got 162 different articles which were sorted by relevance. In Emerald insight I got 675 articles that were sorted by relevance.

From the different platforms, I found many articles that were relevant for my research, and they range between 1980 and 2023. The problem I chose to assess is very new and connected to the usage of the internet. The articles chosen to use are evenly spread over the prior years and had a peak in 2022. The articles also cover several different fields, which gave me a better overview of the topic, but the scope may be limited.

4.2. Research strategy

“By a research strategy, we simply mean a general orientation to the conduct of business research” (Bell et al., 2019, p. 35). I chose to use a quantitative research strategy, where data is being collected in numerical form and emphasizes quantification of data (Bell et al., 2019). In this way I am able to quantify and measure social phenomena and the relationship between them (Bell et al., 2019, p. 163). This research strategy gives me the opportunity to collect data from a vast population, which allows me to achieve a high degree of generalizability for my master's thesis. When it comes to the reasoning of deductive or inductive research approaches, the abductive reasoning starts with the observation of phenomena and then seeks to develop explanations for them. This is often by working between theory and data (Bell et al., 2019, p. 589). Since a quantitative approach is being used in this study, the abductive approach is deemed most appropriate. Abductive reasoning focused on situations or aspects that can differ from the results of the investigation, producing a noticeable gap between certain instances and circumstantial factors.

4.3. Research Design

This study investigates how return policies and practices affect consumer behavior. The focus in this study will be on consumer behavior, since their behavior towards buying or returning a purchased product is decided from an apparel retailers return policy. This is to investigate how consumers behave towards an apparel retailer's return policy when it comes to leniency and strictness, practices, and performance.

A research design relates to the criteria that are used to evaluate the quality of business research. A research design is, therefore, a framework for generating evidence that is suited both to a certain set of criteria and to the research question that is being addressed. (Bell et al., 2019, p. 44)

A cross-sectional design entails the collection of data on more than one case (usually quite a lot more than one) and at a single point in time in order to collect a body of quantitative or quantifiable data in connection with two or more variables (usually many more than two), which are then examined to detect patterns of association. (Bell et al., 2019, p. 59)

“*Internal validity* is typically weak in cross-sectional research” (Bell et al., 2019, p. 59). This is because this design produce associations rather than findings from

which casual interferences can be unconditionally made (Bell et al., 2019). A design approach that establishes causal relationship to a greater extent is casual research design. “Casual research is used to obtain evidence of cause-and-effect (casual) relationships”(Malhotra, 2019, p. 101). Casual research helps to understand which variables are the cause (independent variables) and which variables are the effect (dependent variables) of a phenomenon (Malhotra, 2019, p. 101). Casual research requires a planned structured design in which the casual or independent variables are manipulated in a controlled environment (Malhotra, 2019). Since I cannot control my independent variables and how they affect consumer behavior towards apparel retailers return policy, a cross-sectional research design is most suitable.

By using cross-sectional research design, I am able to detect patterns on how consumers behave towards apparel retailers return policy when it comes to consumers return decision and to what extent they agree with the apparel retailer’s choice of return practice. The method that will be used in this thesis is survey. For this a reason, a standardized and systematic approach is important when investigating associations between various variables (Bell et al., 2019).

4.4. Sampling strategy

A sample is “the segment of the population that is selected for investigation”(Bell et al., 2019, p. 188). Since my survey was shared on social media channels such as Instagram, Snapchat, Facebook, and LinkedIn, it would be very difficult and time consuming to investigate a selected population, because the survey was suitable for all people in all different age groups within Norway. Bell et al., (2019) explain population as the universe of units from which a sample is being selected.

4.5. Survey development

The first part of the questionnaire included factors related to the category variables where there were questions related to categorizing respondents. In this part the author collected information about the respondents in terms of gender, age, and their highest finished education.

In the second part of the questionnaire included category variables where there were questions related to lenient return policy. In this part the author collected information based on respondents answer on returns under any circumstance, relatively length of return period and acceptance of returns due to consumers preferences or expectations.

The third part of the questionnaire included factors related to the category variables related to strict return policy. In this part information was collected by the author based on respondents answer on gatekeeping practices, specific and clear return service explanations, purchase decision and recommendation of apparel retailers.

The fourth part of the questionnaire included category variables where there were questions related to practices. In this part the author has collected information based on the respondents answer on size guides and detailed product descriptions and apparel retailers' impact on consumers purchase decision.

In the fifth part of the questionnaire included category variables where there were questions related to return decisions. Return decision is the dependent variable. The author collected information based on the respondents answer on knowledge about apparel retailers return policy, their keep intention, purchase decision based on apparel retailers practice of return policy and their purchase decision based on the time window for returning a product.

In the sixth part of the questionnaire included category variables where there were questions related to performance. The information was collected by the author based on the respondents answer on sustainable practices, returns due to poor product quality and apparel retailers' performance.

The questions with statements were divided into 6 pages, making each page easy to follow. The dependent and independent variables were placed on a separate page in the questionnaire. This was done so that a variable may be provided with additional information if certain situations or terms required extra explanations.

Translating items from English to Norwegian was a challenge and could be considered as a limitation. The translation was done for all items in this study. For it to be correct, the author had to rewrite the items from English to Norwegian so that the items were correctly formulated. I had several meetings with my supervisor Bente Merete Flygansvær when it comes to ensuring that the items were formulated correctly from English to Norwegian.

In this study a 5-point Likert's scale was used to measure all items within each variable. For the variables Lenient Return Policy and Return Decision, respondents were asked "To what extent do you agree with the following statements". The scale ranged from 1="strongly disagree", to 5="strongly agree" (Bell et al., 2019). For

the variables strict return policy, practices and performance ranged from 1= “to a very low extent” to 5= “to a very large extent”. The 5-point Likert’s scale was applied to all variables, so that the data analysis could be done in the same way and the results could be easily compared.

It is wise to use already established scales to maintain good reliability and validity in this study. It is advantageous to use already established scales to maintain robust reliability and validity in research. These scales, have most likely been examined for reliability and validity testing, which provide a trustworthy framework for data collecting and analysis (Bell et al., 2019).

4.5.1. Operationalization of Variables

It has been long debated whether questionnaire items should be totally positive or a mix of positive and negative items in the literature. One proposal from researchers is to use both favorably and negatively phrased items to reduce response bias (Sonderen et al., 2013). A questionnaire with both positive and negative questions can result in reduced reliability, factor loadings, and validity (Agarwal, 2011). Including negative elements poses several challenges (Salazar, 2015). By including both positive- and negative elements will put the respondents in a situation where they are often unable to answer the questionnaire correctly, and this occurs for several reasons (Salazar, 2015). This is because respondents often fail to recognize the negative words in the sentences when reading the statements because they are positively worded (Sonderen et al., 2013). Secondly, the introduction of negative items frequently causes respondent perplexity owing to increased interpretative complexity, especially when the statements differ from the respondents' current condition or perspective (Sonderen et al., 2013).

By including questionnaire which contain direct and reverse items decrease the reliability and lowers the score for reverse items (Vigil-Colet et al., 2020). For this reason, the author has tried to have the items positively worded to increase the reliability.

The variables in table 1 were designed to categorize respondents, based on their gender, age and highest finished education. This is to classify the respondents that have answered this survey.

Table 1: Questionnaire items for categorizing respondents

Item	Questions	Source
Gender_1	What gender are you?	(Wang et al., 2019)
Age_1	What is your age?	(Wang et al., 2019)
Education_1	What is your highest finished education?	(Wang et al., 2019)
Clothes_online_1	To what extent do you buy clothes online?	Self-developed
Apparel_retailers_1	Can you name 3 clothing retailers from which you last bought clothes online?	Self-developed

Lenient return policy

The variable lenient return policy was chosen to investigate to what extent it influences the level of consumers return decision as part of apparel retailers return policy in the Norwegian market. The variable is inspired from the article by Wang et al., (2019).

Question: To what extent do you agree with the following statements regarding lenient return policy?

Table 2: Questionnaire items for Lenient Return Policy

Item	Item description	Source
LP_1	The platform returns the goods in original price under any circumstances.	(Wang et al., 2019)
LP_2	The platform permits a relatively long period for returning commodities?	(Wang et al., 2019)
LP_3	The platform takes charge of the shipping fee of returning the commodities under any circumstance?	(Wang et al., 2019)
LP_4	The platform accepts the returns due to consumers' preferences	(Wang et al., 2019)

	or inconsistent expectations?	
LP_5	Apparel retailers return service staff understand consumers' needs and requests for returns?	(Wang et al., 2019)

Strict return policy

Strict return policy is the second variable chosen to investigate to what extent this policy influences consumers return decision as a part of apparel retailers return policy in the Norwegian market. This variable is based on inspiration from the research papers Hjort et al., (2019) and Wang et al., (2019).

Question: To what extent do you agree with the following statements regarding strict return policy?

Table 3: Questionnaire items for Strict return policy

Item	Questions	Source
SP_1	Gatekeeping practices are fair and reasonable.	(Hjort et al., 2019)
SP_2	Apparel retailers provide specific and clear return service explanations.	(Wang et al., 2019)
SP_3	I do not purchase apparel products online from a retailer that applies a strict return policy?	(Wang et al., 2019)
SP_4	Would you introduce or recommend an apparel retailer which applies a strict return policy to your friends?	(Wang et al., 2019)
SP_5	To what extent do you agree with clothing retailers that use strict return practices?	(Wang et al., 2019)

Practices

The variable is designed to describe to what extent apparel retailers practice influence consumers return decision in the Norwegian market. The variable was based on inspiration from the research papers Hjort et al., (2019) and Gomes De Oliveira et al., (2022).

Question: To what extent do you agree with the following statements regarding practices?

Table 4: Questionnaire items for Practices

Item	Questions	Source
Practices_1	Size guides and detailed product descriptions, can help consumers to make more informed decisions.	(Hjort et al., 2019)
Practices_2	I believe that organizations should have mandatory environmental care practices.	(Gomes De Oliveira et al., 2022)
Practices_3	Apparel retailer's customer services have a significant impact on consumers purchase decision.	(Hjort et al., 2019)
Practices_4	I would pay more for sustainable products.	(Gomes De Oliveira et al., 2022)
Practices_5	Customers are more likely to purchase apparel products online if they know they can return it without a charge.	(Hjort et al., 2019)

Return decision

“An independent variable is understood as potentially having a casual influence on dependent variables” (Bell et al., 2019, p. 47). The goal is to explain the depended variable with the help of the independent variable. In this case return decision is

chosen as the dependent variable to investigate to what extent the independent variables such as return policies (lenient and strict) and practices influence consumers return decision. Return decision could have an impact on retailers' performance. The dependent variable was based on inspiration from the research papers Gelbrich et al., (2017) and Yu & Kim, (2019).

Question: To what extent do you agree with the following statements regarding return decision?

Table 5: Questionnaire items for Return decision

Item	Questions	Source
RD_1	I know a lot about online stores' return policies.	(Gelbrich et al., 2017)
RD_2	It is very likely that I will order clothes from apparel retailers' online shop as long they offer returns.	(Gelbrich et al., 2017)
RD_3	I usually keep the products I have bought online.	(Gelbrich et al., 2017)
RD_4	Have you ever decided not to make a purchase from a retailer because of their return policy?	(Gelbrich et al., 2017)
RD_5	The time window to return a product is crucial for me before I decide to make a purchase.	(Yu & Kim, 2019)

Performance

This variable is set to describe to what extent return decision influence performance. This variable is not based on an established scale and has for this reason been based on inspiration from the research papers Gomes De Oliveira et al., (2022), Yuen & Chan, (2010), Jack et al., (2010), Hjort et al., (2019) and Griffis et al., (2012).

Question: To what extent do you agree with the following statements regarding performance?

Table 6: Questionnaire items for Performance

Item	Questions	Source
Performance_1	I could observe that sustainable practices are widely publicized in the media.	(Gomes De Oliveira et al., 2022)
Performance_2	Consumers are more likely to return a product if the quality of the product is poor.	(Yuen & Chan, 2010)
Performance_3	Retailers' product and service development is based on customer-focused information.	(Jack et al., 2010)
Performance_4	Apparel retailers can improve their performance by looking at customers' feedback.	(Hjort et al., 2019)
Performance_5	I believe that online retailers see a higher level of product returns than conventional retailers and that the cost of processing these returns is higher.	(Griffis et al., 2012)

Satisfaction

The purpose of this variable is to describe to what extent consumers are totally satisfied with apparel retailers online return schemes and to what extent they buy clothes online. This variable is not based on an established scale and has for this reason been based on self development.

Question: To what extent do you agree with the following statements regarding satisfaction?

Table 7: Questionnaire items for satisfaction

Item	Question	Source
Satisfaction_1	To what extent are you satisfied with apparel	Self-developed

	retailers' online return schemes?	
Satisfaction_2	To what extent will you continue to buy clothes online?	Self-developed

4.5.2. Pilot-test

“The main purpose of a pre-test is to verify the target audience understands the questions and proposed response options as intended by the researcher, and is indeed able to answer meaningfully” (Perneger et al., 2014, p. 147).

The survey for this study was pilot tested on a small sample which consisted of 5 participants. One of the participants was Bente Merete Flygansvær, who is the supervisor for this thesis. The four others were master and bachelor students at BI Norwegian Business School. Performing a pilot test allowed the author to collect feedback to improve and change questions in the survey. The supervisor also advised the author to change the question template from a linear scale that contained 26 questions, to a matrix template. The matrix template ranges between 3 to 5 items consisting of one question where the participants only have one checkbox option.

4.5.3. Data collection

The author used Nettskjema to create and share the survey, where it was anonymous. The only persons that had early access to the survey were the author of the master thesis and his supervisor Bente Merete Flygansvær. To collect the necessary data, the author chose to share the survey through different social media channels. The survey was shared through a link from Nettskjema as a story on Instagram and Snapchat, where it contained information on what the study is about (See 8.1. Appendix 1 – Cover letter). On the social media platform Facebook, the survey was shared as a post containing the link and information from the cover letter (See 8.1. Appendix 1 – Cover letter) on the author’s page.

The survey was sent via email on one occasion, and that was from the author to his supervisor, because she was going to share the survey via link to her working colleagues.

The author's parents also shared the survey as post on their Facebook page and sent the survey as a message to their friends on the social media platform Facebook. Their posts and messages also included the information from the cover letter.

The cover letter explained the purpose and goal of the study, and that the survey was completely anonymous where no personal information was needed from the respondents. The author also explained that the collected data from the survey would only be used for scientific purposes.

4.5.4. Response rate

Response rates can be boosted by several strategies. One of the strategies is that incentives can increase response rates in online surveys (Bell et al., 2019, pp. 203–204). By including a good cover letter which contains relevant information of the study is a widely used method to boost response rates (Bell et al., 2019).

For this reason, I chose to write the information about the survey as an email format. This will show the persons that get exposed to the sharing that it is done for serious and important reasons. It was emphasized that the responses will be anonymous and that participation in the study is voluntary. I also chose to add that it would be highly appreciated if they chose to share the questionnaire. I posted the survey on my social media channels Instagram, Snapchat and Facebook on the 26th of May 2023. One week after I had posted the survey, there were a total of 105 respondents on the questionnaire. Because the questionnaire was shared at the end of May, the time of the distribution could have an impact, as I was shorter on time than a regular research project. Based on this the author was satisfied with the response rate.

4.5.5. Preparing data for analysis

Nettskjema was used to collect the relevant data, and it was transformed to Microsoft Excel, where some of the data had to be cleaned. Two of the 105 respondents answered the questionnaire frivolously, and their data was for this reason removed. Other than that, the data did not consist of any missing answers since all the questions in the survey were mandatory. By providing mandatory questions, it eliminates the possibility of incomplete questionnaires. After processing the data cleaning, the data was transferred to the coding programs RStudio and IBM SPSS for analysis.

All variables and items were given a name representing which variable they belonged to (shown in table 8), and to make the analysis process in RStudio and IBM SPSS clearer. To show two examples, the variable Lenient Return Policy was identified with the acronym LP, and the associated items were labeled as LP_1, LP_2, LP_3 and so on. Strict Return policy was identified with the acronym SP, and the associated items were labeled as SP_1, SP_2, SP_3 and so on. For the variable Performance, the author chose to identify this variable with the acronym Performance_1 to Performance_5_2. This is because there are two questions connected to the item Performance_5. This was easy to accomplish since Nettskjema includes a function where the author can write all the acronyms in a codebook and export this as a file containing data to RStudio and IBM SPSS. To some of the variables I chose to keep the original name, since it would make it much easier when it comes to the analyzing part. All the acronyms are shown in table 8.

Table 8: Variable labels

Variable	Label
Lenient return policy	LP
Strict return policy	SP
Practices	Practices
Return decisions	RD
Performance	Performance
Satisfaction	Satisfaction

4.6. *Quality of research*

The most popular and commonly used criteria for evaluating the quality of a research study are validity, reliability, and replicability (Bell et al., 2019). “[...] validity is concerned with whether a measure captures the phenomenon which it is intended to capture” (Bell et al., 2019, p. 46). Since the items in the questionnaire were based on inspiration from previous research articles, ensures that the items are based on established theories and concepts. This could display that the items satisfy content validity (Privette & Bundrick, 1987).

To calculate the sample characteristics of the respondents, I used Microsoft Excel. In section 5.1, the author presents sample characteristics of respondents. In Section 5.3 of this study, the author assessed the construct validity through a factor analysis.

This analysis sought to investigate the underlying factor structure and confirm that the measurement items captured the intended constructs adequately. Additionally, in Section 5.5, the author used Cronbach's alpha (α) to assess the internal consistency of each variable during reliability testing. These reliability evaluations estimated the consistency and reliability of the measurement scales utilized in the study. The path analysis was conducted in the statistical program RStudio (see Appendix 4 – Multiple regression and path analysis). Furthermore, this thesis gives complete and precise explanations of all methods done.

5. Results

5.1. Sample characteristics

Table 9 shows that 54.37% of the respondents were male and that 45.63% of the respondents were female. This could imply that the sample is slightly skewed, with a greater number of responses came from men.

		<i>Frequency</i>	<i>Percent</i>
Gender	Male	56	54.37%
	Female	47	45.63%

Table 9: Respondents based on gender

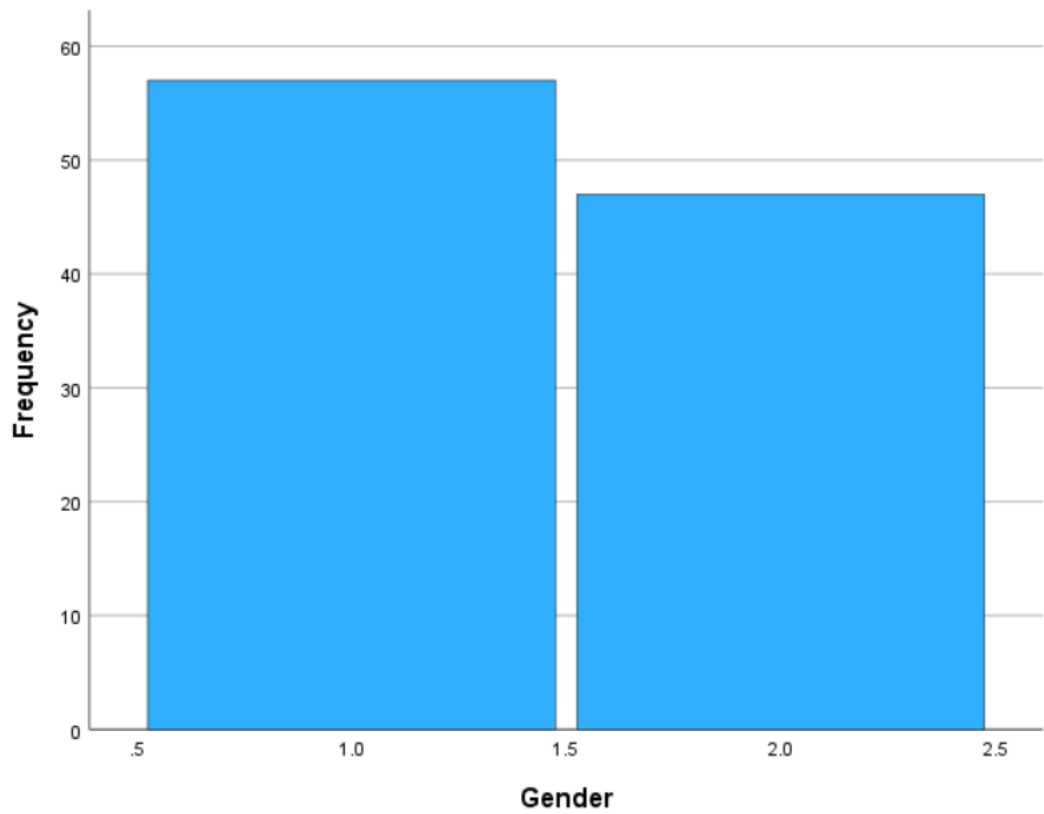


Figure 3: Histogram based on respondents' gender, where N = 103

Table 10: Respondents sorted into different age groups

Age groups	Frequency	Percent	Mean age	Median age
			41.64	41.50
Under 18	1	0.97%		
18-19	0	0.00%		
20-29	42	40.78%		
30-39	7	6.80%		
40-49	6	5.83%		
50-59	37	35.92%		
60-69	5	4.85%		
70-79	4	3.88%		
80 and above	1	0.97%		
Total	103	100.00%		

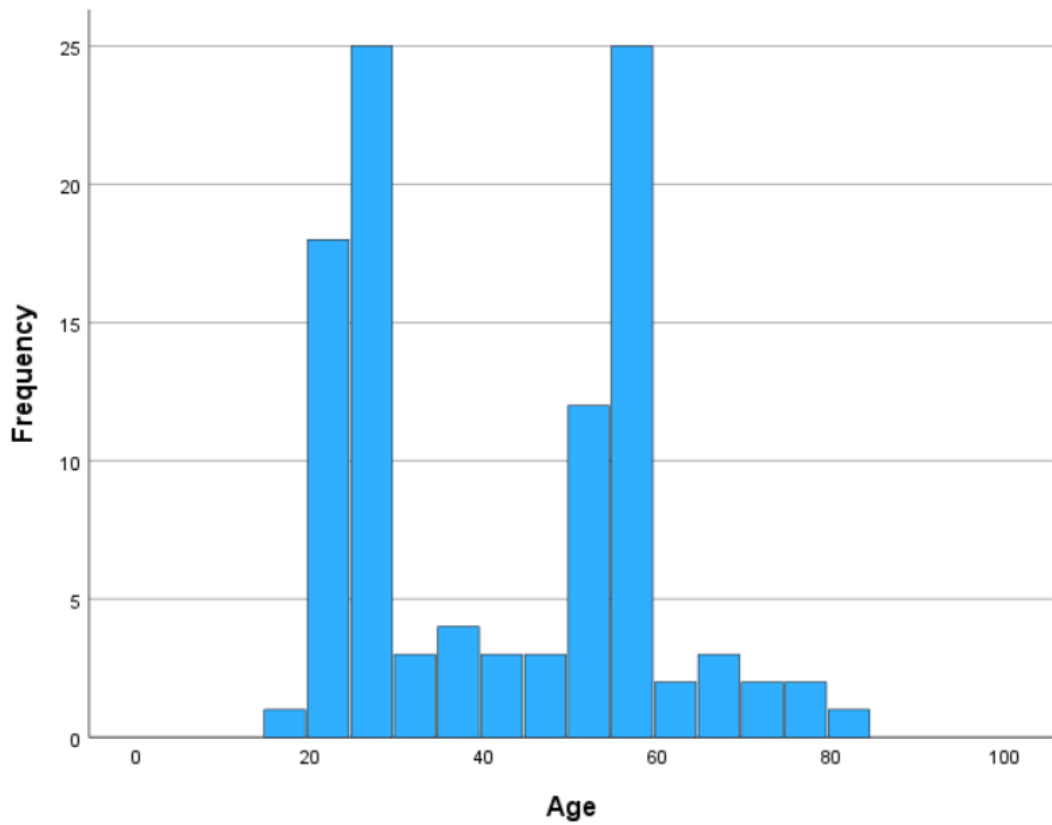


Figure 4: Histogram with normal distribution based on age (N =103)

From the normal distribution above, most of the respondents were in their middle 20s and middle 50s. It is positive that people ranging from age 18 to age 80 answered the survey.

Highest finished education	Frequency	Percent	Mean	Median
			2.59	3.00
High school degree or lower	28	27.18%		
Technical school	12	11.65%		
Bachelor degree	37	35.92%		
Master degree	25	24.27%		
Doctoral degree (PHD)	1	0.97%		
Total	103	100.00%		

Table 11: Highest finished education

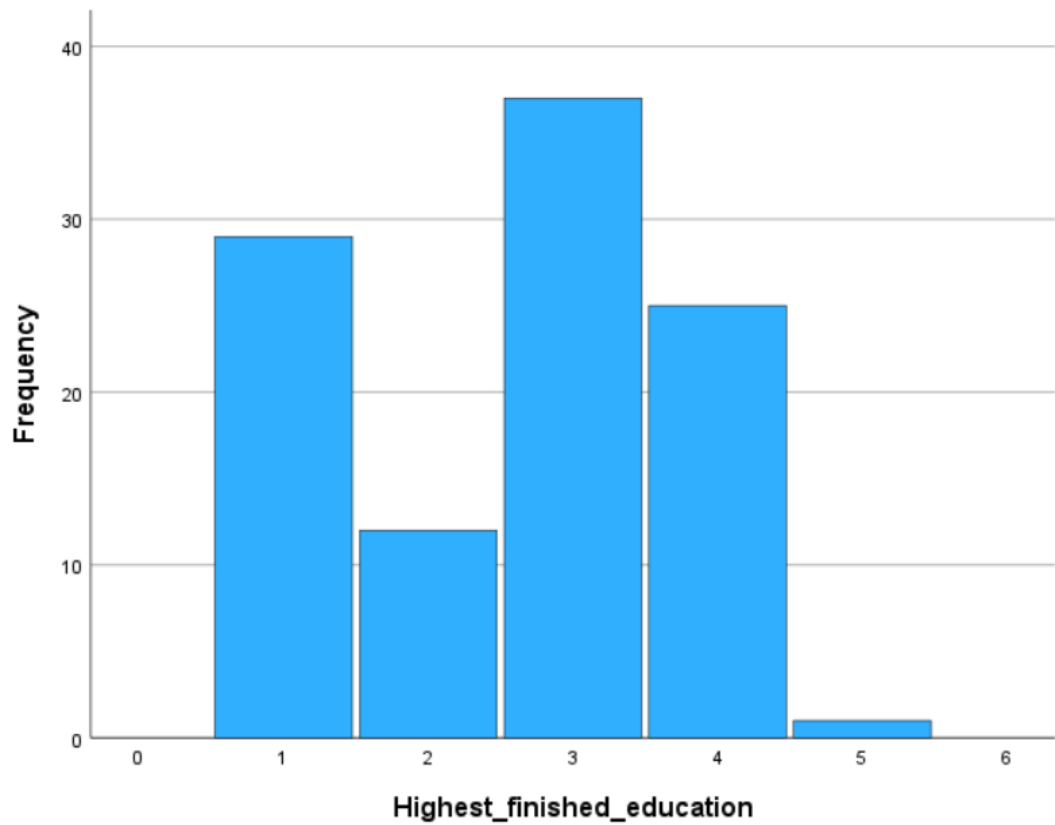


Figure 5: Histogram of highest finished education. (N = 103)

Another important element that makes the answer from the respondents unbiased is that the questionnaire has reached out to people with different educational backgrounds. If a large percentage of the respondents had one certain educational background, there would have been a skewness of respondents with similar educational background.

Most named apparel retailers	<i>Frequency</i>	<i>Percent</i>
Zalando	46	44.23%
Zara	15	14.42%
Boozt	8	7.69%
Cubus	7	6.73%
Ellos	4	3.85%
Follestad	3	2.88%
Volt	2	1.92%

Table 12: Most named apparel retailers

Table 12 clearly shows that most respondents buy clothes online from Zalando, Zara, Boozt, and Cubus, since these were the most cited. Of all the answers two

Norwegian apparel retailers were mentioned 5 times, where Follestad was mentioned three times, and Volt was mentioned 2 times.

5.2. *Skewness and kurtosis*

[Skewness] Measure of the symmetry of a distribution; in most instances the comparisons is made to a *normal distribution*. A positively skewed distribution has relatively few large values and tails off to the right, and negatively skewed distribution relatively small values and tails off to the left. Skewness values falling outside the range of -1 to +1 indicate substantially skewed distribution. (Hair et al., 2019, p. 48)

To assess the normality of the collected data, I conducted an examination of the skewness and kurtosis metrics for each individual variable. These variables are shown in table 13. “[Kurtosis] Measure of the peakedness or flatness of a distribution when compared with a *normal distribution*. A positive value indicates a relatively peaked distribution, and a negative value indicates a relatively flat distribution” (Hair et al., 2019, p. 48). Table 13 shows quite clearly that the items LP_4, Practices_1, RD_3 and RD_4 have a relative high kurtosis, because their values exceed 1. The item with the highest kurtosis is Practices_5 with a value of 4.569. This is highlighted in table 13 on page 35.

Descriptive Statistics

	N	Skewness	Kurtosis
LP_1	103	-.995	.466
LP_2	103	-.431	-.195
LP_3	103	-.537	-.595
LP_4	103	-1.386	1.899
LP_5	103	-.717	.299
SP_1	103	-.381	.138
SP_2	103	-.906	.668
SP_3	103	-.064	-.534
Strict_return_policy_introdu ce_retailer (SP_4)	103	.319	-.518
Agree_with_retailer_strict_ policy (SP_5)	103	.341	-.496
Practices_1	103	-1.387	2.273
Practices_2	103	-.713	.889
Practices_3	103	-.950	.958
Practices_4	103	-.244	-.896
Practices_5	103	-1.918	4.569
RD_1	103	-.200	-.466
RD_2	103	-.474	-.202
RD_3	103	-.705	1.208
RD_4	103	.222	-1.078
RD_5	103	.078	-.747
Performance_1	103	.142	.162
Performance_2	103	-.222	-.136
Performance_3	103	.089	-.272
Performance_4	103	.137	-.951
Performance_5_1	103	-.554	.055
Performance_5_2	103	-.303	-.084
Satisfaction_1	103	-.662	.756
Satisfaction_2	103	-.980	.233

Table 13: Skewness and kurtosis metrics for each variable

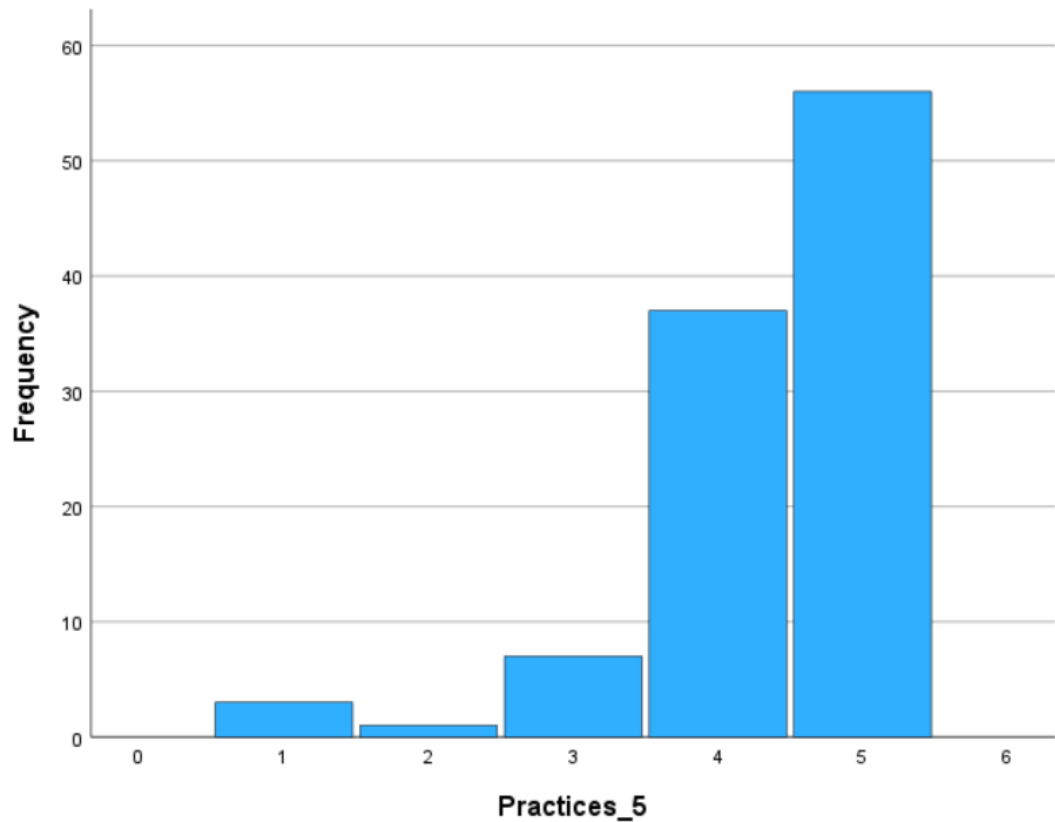


Figure 6: Histogram of respondents answer on item Practices_5

The item Practices_5 represents the statement “*Customers are more likely to purchase apparel products online if they know they can return it without a charge*”. Figure 6 makes it abundantly evident that the normal distribution is negatively skewed since the data collection's peak is on the right side and its longer tail is on the left.

Hae-Young Kim (2013) states that the acceptable levels of a given parameter are contingent upon the size of the sample (H.-Y. Kim, 2013). Patrick J. Curran, John F. Finch and Stephen G. West (1996) state that several researchers accepted skewness ≤ 2 and kurtosis ≤ 7 as acceptable values (Curran et al., 1996). “For some practical reasons, most statistical packages such as SPSS provide ‘excess’ kurtosis obtained by subtracting 3 from the kurtosis (proper)” (H.-Y. Kim, 2013, p. 53). Other researcher come with a statement that a skewness value < 3 and a kurtosis value < 10 are acceptable. This means that I had to add the number 3 to the value that was extracted from IBM SPSS. The proper kurtosis value would then be $4.569 + 3 = 7.569$. This value was lower than some researchers’ acceptable value. For this reason, the skewness value and kurtosis value of item Practices_5 was acceptable.

5.3. Factor analysis

The process of construct validation is a complex and multifaceted undertaking that involves three fundamental steps (O’Leary-Kelly & J. Vokurka, 1998, p. 389). “Construct validity refers to the degree to which inferences can legitimately be made from the operationalizations in a study to the theoretical constructs on which those operationalizations were based” (Agarwal, 2011, p. 1). In the first stage, a group of empirical indicators that are believed to measure the construct must be identified. It is necessary to demonstrate that the empirical indicators are logically and theoretically connected with the construct (O’Leary-Kelly & J. Vokurka, 1998). Researchers referred to the first step as content validity. Step two determines the extent to which the empirical indicators measure the construct. The third step of the research process entails the evaluation of the degree to which a given construct exhibits a predictable association with other constructs, thereby entailing the process of hypothesis testing (O’Leary-Kelly & J. Vokurka, 1998).

Factor analysis is employed in relation to multiple-indicator measures to determine whether groups of indicators tend to bunch together to form distinct clusters, referred to as factors. Its main goal is to reduce the number of variables with which the researcher needs to deal. It is used in relation to multiple-item measures, such as Likert scales, to see how far there is an inherent structure to the large number of items that often make up such measures. (Bell et al., 2019, p. 183)

For this reason, the author chose to use an exploratory factor analysis by giving insight into the structure of the questionnaire, where he is examining the correlations between the observed measures is the guiding principle of factor analysis.

5.3.1. KMO and Bartlett’s test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.	.701	
Bartlett's Test of Sphericity	Approx. Chi-Square	1063.593
	df	325
	Sig.	<.001

Table 14: KMO and Bartlett’s Test

Before proceeding with an exploratory factor analysis, I conducted a series of straightforward tests to determine whether the data were suitable for factor analysis. The author began by examining the Kaiser Meyer-Olkin (KMO) measure. “From the KMO index of sampling adequacy, values above .6 are required for good factor analysis” (Dugard et al., 2010, p. 186). Table 14 on page 37 demonstrates that the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy produced a value of 0.701. This value indicates an acceptable level of partial correlations in the data set. Secondly, the author examined Bartlett's Test of Sphericity, where the p-value should be less than 0.05 to be statistically significant (Yong & Pearce, 2013, p. 88). From the table 14 on page 37, Bartlett's Test produced a p-value of ($p < .001$), which indicates that there exists a patterned relationship among the variables. Based on this information, it is evident that the data is acceptable to conduct an exploratory factor analysis.

5.3.2. Exploratory factor analysis

The second part of the exploratory factor analysis was to perform three factor matrix containing different benchmarks, that ranged from 0.30 to 0.55. This was performed by using the Maximum Likelihood extraction method and the Varimax rotation method, where the only values that were extracted had an Eigenvalue ≥ 1 , due to the eigenvalue criterion.

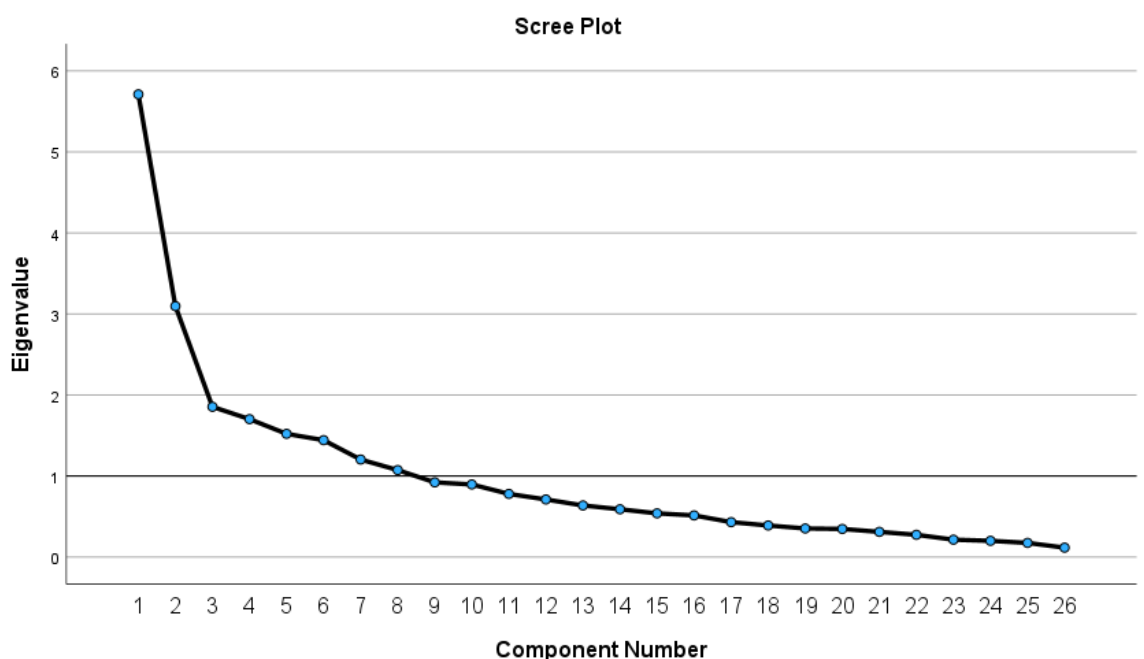


Figure 7: Scree plot

After the scree plot was investigated, an exploratory factor matrix was conducted in IBM SPSS, containing a benchmark of 0.30 and five factors. These factors are *Lenient return policy*, *Strict return policy*, *Practices*, *Return decision* and *Performance*.

Table 15: Exploratory factor analysis with a benchmark of 0.30.

Exploratory Factor Analysis - Factor Matrix^a

	Factor				
	1	2	3	4	5
LP_1	.816				
LP_2	.568				
LP_3	.643				
LP_4	.715				
LP_5	.727	.339			
SP_1	.423	.512			
SP_2	.571	.425			
SP_3			-.517		
Strict_return_policy_introdu ce_retailer (SP_4)			.750		
Agree_with_retailer_strict_ policy (SP_5)			.838		
Practices_1	.327	.634			
Practices_2					.860
Practices_3	.340	.318			
Practices_4					.621
Practices_5	.393	.436			
RD_1		.319		.510	
RD_2		.365			
RD_3		.367			
RD_4			-.451	.746	
RD_5				.815	
Performance_1					
Performance_2				.303	
Performance_3					
Performance_4		.350			
Performance_5_1		.326			
Performance_5_2		.344			

Extraction Method: Maximum Likelihood.

Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 6 iterations.

Convergent validity reflects to the extent to which two measures capture the same information (Carlson & Herdman, 2012, p. 19). A benchmark of 0.30 was chosen to include all the values from the different items. From table 15 above, it is quite

clear that four of the five items of LP had high positive loadings on factor 1, while LP_5 is the only item from LP that had a cross-loading on factor 2.

The items SP_1 and SP_2 had a cross-loading on factor 3, while the items SP_3, SP_4 and SP_5 only had a loading on factor 3. There is most likely an underlying factor that is associated with the items SP_1 and SP_2.

The items Practices_1, Practices_3 and Practices_5 contained cross-loading for factor 1 and factor, while Practices_4 and Practices_5 contained a positive loading on factor 5.

When it came to the items in Return decisions, RD_1 had a positive loading on factor 2 and factor 4. RD_4 had a negative loading on factor 4 and a highly positive loading on factor 5. The items RD_2 and RD_3 had a low positive loading on factor 2. The item RD_5 had a high positive loading on factor 4.

When it comes to the items Performance_1 and Performance_3, their value is not included in the table, because it did not pass the benchmark of 0.30. Performance_2 had a low positive loading on factor 4, while the items Performance_4, Performance_5_1 and Performance_5_2 had a low positive loading on factor 2.

When it comes to the cross-loading items from the different variables (see Table 15 on p. 39), it indicates that the items most likely are associated with more than one underlying factor. Such discrepancies may arise either because of respondents' inherent ambiguity in applying the item's meaning or because the item is related to more than one underlying component. It is advisable to exercise caution when interpreting these findings. The results obtained from the factor analyses conducted on an individual basis are presented in Appendix 8.4.

5.3.3. Final exploratory factor analysis

Establishing a factor loading threshold is a crucial aspect of conducting a factor analysis, as it determines the inclusion of an item within a given factor. The researchers Joseph F. Hair JR., William C. Black, Barry J. Babin and Rolph E. Anderson stated that the benchmark for determining the significance of factor loadings is contingent upon the size of the sample (Hair et al., 2019). Since I received 105 respondents, the appropriate benchmark for a significant factor loading is 0.55. As a result, when running the factor analysis, I applied a setting in IBM SPSS not to show factor loadings below the benchmark of 0.55.

Table 16 shows the factor analysis, where only 13 out of 26 items passed the benchmark of 0.55. All the items from LP_1 to LP_5 passed the benchmark, with a positive loading on factor 1. When it comes to the items in SP, only SP_2, SP_4 and SP_5 passed the benchmark. SP_2 had a positive relationship on factor 1, while SP_4 and SP_5 had a highly positive relationship on factor 3.

For the items in Practices, only Practices_1, Practices_2 and Practices_4 passed the benchmark. Practices_1 has a positive relationship on factor 2, while Practices_2 has a strong positive relationship with factor 5.

Regarding the items in RD, only RD_4 and RD_5 passed the benchmark, and it seems that both items had a strong positive relationship on factor 5.

Table 16 below indicates that none of the items in Performance passed the benchmark. Discrepancies may arise due to the inherent ambiguity in respondents' application of the item's meaning. This could indicate that some of the items should have been removed, but the author chose not, since the items were used in the path analysis. For this reason, it is highly recommended to exercise prudence when interpreting these findings.

Exploratory Factor Analysis - Factor Matrix^a

	Factor				
	1	2	3	4	5
LP_1	.816				
LP_2	.568				
LP_3	.643				
LP_4	.715				
LP_5	.727				
SP_1					
SP_2	.571				
SP_3					
Strict_return_policy_introdu ce_retailer (SP_4)			.750		
Agree_with_retailer_strict_ policy (SP_5)			.838		
Practices_1		.634			
Practices_2					.860
Practices_3					
Practices_4					.621
Practices_5					
RD_1					
RD_2					
RD_3					
RD_4				.746	
RD_5				.815	
Performance_1					
Performance_2					
Performance_3					
Performance_4					
Performance_5_1					
Performance_5_2					

Extraction Method: Maximum Likelihood.
 Rotation Method: Varimax with Kaiser Normalization.
 a. Rotation converged in 6 iterations.

Table 16: Exploratory factor analysis with a benchmark of 0.55.

5.4. Descriptive statistics -Variables

The study's descriptive statistics for each variable are presented in Table 17. The computation of the variables involved the calculation of the mean of the individual items that constituted each variable. The rationale behind selecting this approach was due to the fact that all the variables under investigation in the study were composed of multiple items.

The computation of the mean of the items yields a representative measure that encapsulates the central tendency of each variable. This facilitates a more lucid comprehension of the comprehensive attributes and patterns inherent in each variable.

Employing multiple items within a variable facilitates the comprehensive representation of the diverse dimensions or facets of the constructs being examined. The computation of the mean by combining the individual item scores results in a composite measure that represents the overall level or inclination of the variable.

This approach guarantees the precise representation of variables and the provision of significant insights into the data through descriptive statistics. The calculation of means for the items in the study serves as a succinct representation of the central tendency of each variable, thereby enabling a thorough examination and elucidation of the research results. In this master thesis, the utilization of mean calculation for each variable, based on the constituent items, contributes to the improvement of both the reliability and comprehensiveness of the data analysis.

The primary objective of utilizing factor analysis is to investigate the interrelationships between the variables, evaluate their potential connection with latent factors, and determine if they exceed the predetermined threshold loading values. The present analysis facilitates a thorough comprehension of the interrelationships among the items and assists in revealing the underlying framework of the assessed constructs (O’Leary-Kelly & J. Vokurka, 1998).

All variables included in this study are deemed essential for conducting the subsequent path analysis within the framework presented in Figure 2: Research Model. No exclusions have been made. Further elaboration on the analysis details will be provided in section 5.6, which covers multiple regression and path analysis. A comprehensive outline of detailed descriptive statistics for each item within every variable can be found in Appendix 8.3.

Descriptive statistics				
	N	Mean	Std. Deviation	
	Statistic	Statistic	Standard Error	Statistic
LP	103	3.783	.0813	.8296
SP	103	3.058	.0518	.5278
Practices	103	3.812	.0605	.6168
RD	103	3.154	.0646	.6585
Performance	103	3.514	.0457	.4668
Satisfaction	103	3.630	.0893	.9111

Table 17: Descriptive statistics for all variables

5.5. Cronbach’s Alpha

“Reliability refers to the consistency of a measure of concept” (Bell et al., 2019, p. 172). The absence of reliability in an outcome measure is a significant limitation, as it suggests errors in the measurements (Spiliotopoulou, 2009). To evaluate the

internal consistency of the variables, a Cronbach's alpha (α) test was performed on each variable. This widely acknowledged metric estimates the reliability and consistency of the items within each variable. In the following section, the results of the Cronbach's alpha test will be discussed in greater depth.

Cronbach's alpha is a commonly used test of internal reliability. It calculates the average of all possible split-half reliability coefficients. The α coefficient is a statistical measure that estimates the degree of systematic variance or true score of a given measure, with values ranging from 0 to 1. The measure is derived through the computation of correlations among its constituent indicators. Elevated Cronbach's alpha coefficients are linked to increased correlations among the indicators (O'Leary-Kelly & J. Vokurka, 1998).

The α coefficient is utilized as a metric to assess the internal consistency or reliability of a measurement. The measure's internal consistency is indicated by the degree to which its constituent items are interconnected and effectively assess the fundamental construct. A higher value of the alpha coefficient indicates a higher degree of intercorrelation among the indicators, which in turn suggests a greater level of internal consistency and reliability of the measure (O'Leary-Kelly & J. Vokurka, 1998).

Through the analysis of alpha coefficients, researchers can assess the extent to which the indicators comprising a given measure exhibit internal consistency and yield reliable measurements of the underlying construct. The coefficients furnish significant insights concerning the dependability and coherence of the metric, facilitating the elucidation and evaluation of the measuring apparatus employed in the study (O'Leary-Kelly & J. Vokurka, 1998).

There is not a complete agreement among researchers on how large the alpha coefficient should be in order to be considered acceptable (O'Leary-Kelly & J. Vokurka, 1998, p. 397). Some researchers conclude that reliability values below 0.70 are not acceptable, while others conclude with that a reliability value of 0.50 is acceptable (O'Leary-Kelly & J. Vokurka, 1998).

Table 18 shows the Cronbach's Alpha coefficient for each variable. As four out of five variables had an alpha coefficient over the benchmark value of 0.50, I consider

them to have an acceptable internal reliability. Higher Cronbach's alpha values indicate higher trust in the measure's reliability and consistency. The only variable that has a good internal reliability is LP, with an alpha value of 0.842. SP has the lowest alpha value of 0.364.

Cronbach's Alpha - Reliability					
	LP	SP	Practices	RD	Performance
Cronbach's Alpha	0.842	0.364	0.636	0.597	0.523
N	5	5	5	5	6

Table 18: Cronbach's Alpha

5.6. Multiple regression and path analysis

5.6.1. Multiple regression

Multiple regressions apply the same ideas to a scenario when there is more than one independent variable. The core principle is that a direct variable may be written as a linear function of one or more indirect variables, which are supposed to be free of random fluctuation plus some random variation (Dugard et al., 2010, p. 84).

The fourth question in my questionnaire was: "*How often do you buy clothes online?*". For this reason, the author wanted to see which of the respondents buy most clothes online based on their age. The author created then an average score on the variable **buying_clothes_online_degree** from the respondents' answer. He also created a variable where he sorted the respondents into different age groups. This variable was called: **age_group**. This was conducted in the statistical program RStudio.

Table 19: Average score on buying clothes online based on age group

Age group	Average score on buying clothes online
Under 18	2
18-19	0
20-29	2,57
30-39	2,71
40-49	3,83

50-59	2,38
60-69	2,2
70-79	2,5
80 and above	1

Table above, indicates that respondents from age 40 to 49 purchase most clothes online compared to the other age groups, even if only 5,82% of the respondents were in this age group. The mean value of the respondents in this group is 3,83. The results from the average scores should be taken with caution, since some age groups had a lot more respondents than others and could for this reason influence the mean values for the different age groups.

Since I only had the respondents age and educational background to categorize them, I wanted to see if age or educational background had an effect on buying clothes online. Thirdly, the respondents were sorted into different groups based on their highest finished education (see Table 11 on p. 33). The variable containing the sorting of respondents' educational background was called **Education**. I continued to use the **age_group** variable for the linear regression.

In the first regression the dependent variable is **Buying clothes online degree**, and the independent variables are **age_group** and **Education**.

Equation 1:

$$\text{Buying clothes online degree} = \beta_0 + \beta_1 * \text{age group} + \beta_2 * \text{Education}$$

Table 20: Residuals from *Equation 1*

Min	1Q	Median	3Q	Max
-1.71551	-0.71437	0.08945	0.54139	2.56974

Table 21: Coefficients from *Equation 1*

	Estimated standard error	t value	Pr(> t)
Intercept	2.00	1.810	0.0737
Age group 20 - 29	0.714	0.630	0.5301

Age group 30 - 39	0.939	0.775	0.4401
Age group 40 - 49	1.943	1.602	0.1126
Age group 50 - 59	0.512	0.450	0.6536
Age group 60 - 69	0.309	0.253	0.8007
Age group 70 - 79	0.748	0.597	0.5518
Age group 80 and above	-1.00	-0.640	0.5239
Technical school	-0.081	-0.204	0.8386
Bachelor degree	-0.0328	-0.114	0.9097
Master degree	-0.48	-1.520	0.1321
Doctoral degree (PHD)	-0.512	-0.450	0.6536

Table 22: Summary of *Equation 1*

Multiple R-squared	Adjusted R-squared	p-value
0.142	0.03833	0.2009

Table 22 displays that the p-value is 0.2009 and adjusted R^2 is 0.03833, which is extremely low. This indicates that I have an extremely low fit, which is not positive at all. From table 21 we see the coefficients from the different age groups and educational backgrounds. None of the variables are statistically significant on any level. The age group that is closest to being statistically significant on a 10% level is the age group 40 – 49 which had a t value of 1.602. This explains that the variables **age_group** and **Education** cannot statistically explain the correlation on the degree of consumers buying clothes online. This indicates that there most likely are other independent variables than the ones I chose to use, that could better explain the correlation on this variable.

5.6.2. Path analysis

The reason why the author chose to conduct a path analysis is because the measurement model consists of two dependent variables (see figure 2 on p. 18). These dependent variables are **RD** (stands for return decision) and **Performance** (apparel retailers' performance). This was conducted in the statistical program RStudio.

Path analysis is an extension of multiple regression. It focuses on the pattern relationships among a set of variables rather than just on which IVs predict a DV and how strongly. It is used to test the fit of casual models against correlation matrices for the variables in the models. (Dugard et al., 2010, p. 159)

Path analysis frequently employs causal modelling, which incorporates the underlying assumptions made by researchers during the construction of their models. The researchers posit causal connections that they deem to be present among the variables being examined. The integration of these presumptions into the model enables path analysis to examine the direct and indirect causal impacts among variables, thereby facilitating a greater understanding of the fundamental causal mechanisms at play (Dugard et al., 2010, p. 159). Path models are evaluated by estimating the parameters indicated by arrows (Dugard et al., 2010) (see figure 2 on p. 18).

Path analysis proceeds by means of a series of regression analysis, beginning with the furthest right variable as the DV and all variables to its left that point at it as IVs. If there is more than one variable at the extreme right of the diagram, each is treated as the DV in turn. (Dugard et al., 2010, p. 162)

“The sequence of regression analysis (moving backwards toward the left) continues until the only remaining independent variable(s) is the exogenous variable(s) at the extreme left” (Dugard et al., 2010, p. 162).

The first step in the path analysis comprised the consolidation of diverse items across distinct factors into a solitary, common variable, thus simplifying the data for further analysis. The common variable consisted of the mean value of all the items in the different variables. Table 23 shows the common variables based on the mean values from the different items.

Table 23: Common variable created from computing the mean values of the different items

Common variable	Mean value
LP	3.777
SP	3.054
Practices	3.812
RD	3.15

Performance	3.516
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The second step was to create a path analysis in RStudio to see if **LP**, **SP** and **Practices** are statistically significant on **RD**, and if **RD** is statistically significant on **Performance**.

Equation 2:

$$Performance = \beta_0 + \beta_1 * RD$$

$$RD = \beta_0 + \beta_1 * LP + \beta_2 * SP + \beta_3 * Practices$$

The variable **Performance** is set to describe to what extent consumers return decision influence apparel retailers performance. From the first regression it is quite clear that the variable **RD** has the statistical capability to explain the correlation that has been observed with the dependent variable **Performance**, because it is statistically significant on 5% level with a z-value of 2.302.

In the second regression from the path analysis, **RD** was chosen as the dependent variable because it catches consumers return decision based on apparel retailers return policy and practices. The output given by RStudio shows that the only independent variable that is statistically significant on 10% level was **Practices**, which had a z-value of 1.777. This implies the possibility of the existence of additional variables apart from **LP** and **SP** that may offer a more comprehensive explanation of the correlation with the specific dependent variable **RD**.

Table 24: Regressions from *Equation 2*

Variables	Estimate	z-value	P(> z)
Performance ~			
RD	0.157	2.302*	0,021*
RD ~			
LP	0.128	1.418	0.156
SP	0.027	0.207	0.836
Practices	0.222	1.777.	0.076.

Note: The . behind the t-value of 1.777 indicates that this variable is statistically significant on a 10% level. The * indicates that the variable is statistically significant on a 5% level.

5.7. Hypotheses testing

H1: *A lenient return policy has a positive influence on consumers' return decision.*

Most of the mentioned apparel retailers by the respondents practice a lenient return policy where the consumer can return the product without a return fee, given that the product is not damaged, washed, has stains or marks. Hypothesis 1 was tested in the path analysis, and the result indicates that H1 is not fulfilled, because the independent variable is not statistically significant on any level.

H2: *Strict return policy is statistically significant and has a positive impact on consumers' return decision.*

The results for H2 showed very clearly that this hypothesis is not fulfilled, since the variable **SP** is not statistically significant on any level. It has a z-value of 0.207, which indicates that this variable explains the effect on consumers return decision to a very low degree. The test for H2 was conducted in the path analysis.

H3: *Practices are statistically significant and have a positive impact on consumers' return decision.*

The results for H3 show that *Practices* is statistically significant on a 10% level, with a $p < 0.10$. Based on my path analysis from the data collection, it is plausible to conclude that *Practices* has a positive impact on consumers return decision.

H4: *Consumers return decision is statistically significant and has a positive impact on apparel retailers' performance.*

With a p-value of 0.05 and a z-value of 2.302, the findings for H4 suggest that *Return decisions* are a predictor of *Performance*. The notion is validated and has a beneficial influence on the performance of apparel retailers.

5.8. Satisfaction

The author wanted to see how satisfied the respondents were with apparel retailers online return schemes and to what extent they will continue to purchase apparel products online. Table 25 below displays that most of the respondents (44.66%) are satisfied with this statement “*To what extent are you satisfied with clothing retailers' online return schemes*” (**Satisfaction_1**), while 34.95% are somewhat satisfied. Only 3.88% of the respondents are not very satisfied with apparel retailers' online return schemes. Satisfaction_1 has a mean value of 3.54, which

signifies that most of the respondents agree with this statement. Regarding the statement “*To what extent will you continue to buy clothes online*” (**Satisfaction_2**), 28.16% of the respondents will continue to purchase clothes online to a very large extent, while 4.85% will continue to buy clothes online to low extent. The mean value (3.72) from Satisfaction_2 signifies that the respondents agreed to a high level with this statement, and that they will continue to purchase apparel products online.

The author would like to conclude that most of the respondents agree with apparel retailers online return schemes and will continue to purchase apparel products to a large extent.

Satisfaction_1	Frequency	Percent	Mean
5 (Very satisfied)	12	11.65%	3.54
4 (Satisfied)	46	44.66%	
3 (Somewhat satisfied)	36	34.95%	
2 (Little satisfied)	6	5.83%	
1 (Not very satisfied)	4	3.88%	
Satisfaction_2	Frequency	Percent	Mean
5 (Very large extent)	29	28.16%	3.72
4 (Large extent)	42	40.78%	
3 (To some extent)	18	17.48%	
2 (Low extent)	5	4.85%	
1 (Very low extent)	10	9.71%	

Table 25: Frequency of consumer satisfaction

6. Discussion

The aim of this research was to investigate whether the independent variables **lenient return policy**, **strict return policy** and **Practices** influenced consumers return decision, but also to see if the dependent variable **return decision** influenced **performance**. This was accomplished through gaining insight into how return policies and apparel retailers’ practices affect return decisions, and how return decision affects apparel retailers’ performance. The author also gained insight on how these affect retailers’ bottom line and logistics. The next section of the master thesis includes the discussion, where the author begins with explaining theoretical implications, to see if the results from this study are in line with the literature. Managerial implications will be discussed in the last part.

6.1. Theoretical implications

The final exploratory factor analysis indicates that all the items for **Lenient return policy** load on one factor and that they passed the benchmark. The result from the path analysis displays that **Lenient return policy** is not statistically significant on **Return decision** since it had p-value of 0.156. This differs from the findings in the literature review, where two of the research papers state that a lenient return policy may serve as a motivating factor for customers to indulge in the behavior of excessive ordering and subsequent returns of products (Gustafsson et al., 2021; Saarijärvi et al., 2017). This phenomenon pertains to the conduct of consumers who initiate the purchase of numerous items in diverse iterations with the objective of subsequently returning the variant(s) that are deemed to be the least suitable (Gustafsson et al., 2021). As a result, the implementation of lenient return policies has been observed to encourage irrational ordering behavior among consumers, leading to a notable increase in return rates. Other researchers have found that lenient return policies can result in a reduction of return shipping expenses for customers and guarantee that discontented customers have the ability to conveniently and economically return defective products (Hjort et al., 2019).

The literature also shows that the volume of returns increases when retailers choose to adopt a lenient return policy. This could indicate that it is very challenging for retailers to handle product returns in several states. It is rare for products that have been returned to undergo repair or receive new packaging (Ramanathan, 2011). This affects apparel retailers inventory management, since the returned products could be sorted into different categories based on products that need to be repaired, given new packaging, or transported for liquidation. The literature review also highlights that this also affects the apparel retailer's ability to handle reverse logistics, because it requires them to establish streamlined procedures to manage the many phases of product returns, such as inspection, sorting, disposal, and potential reintegration into inventory (Ramanathan, 2011). The author chose to look at what consumers think about apparel retailers' lenient return policy.

The findings display that a lenient return policy does not affect consumers return decisions, and that they would return a purchased anyway, without taking the lenient return policy into account. Firstly, it could be that the sample size was very small and biased, and it could have been much larger (Dugard et al., 2010).

Secondly, the return behavior of consumers could be influenced by a multitude of factors that extend beyond the leniency of the return policy. Factors that could influence a consumer's decision to return a product include personal preferences, prior experience with returns, and the perceived level of effort involved in the return process (Lee & Turban, 2001). In certain instances, these factors may surpass the impact of the return policy itself.

The finding related to a lenient return policy highlights the complexity of consumer behavior and emphasizes the importance of considering various factors when analyzing the impact of return policies. The proposition suggests that retailers should not solely depend on the flexibility of their return policy as a means to shape consumer behavior (Bolton et al., 2000). Instead, they should consider additional factors pertaining to their products and services that may exert a more significant influence on customers' choices.

For this reason, the findings for this variable should be viewed with caution since H1 is not fulfilled, and other aspects such as data from apparel retailers or logistical providers were not included in this study.

The findings for the variable **Strict return policy** in the path analysis display that it is not statistically significant on **Return decision** since it had p-value of 0.836. This contradicts with the findings in the literature, since researchers have found that a strict return policy typically encompasses various rules and limitations intended to minimize concerns related to customer exploitation of lenient return policies. This allows retailers to directly communicate with returnees and implement uniform procedures to reduce unjustified returns, ultimately decreasing shipping and warehousing costs (Hjort et al., 2019). The literature reveals that practicing a strict return policy can discourage consumers from purchasing apparel products online (Letizia et al., 2018). This could display fewer consumers requesting returns, thereby reducing the number of items returned, and could simplify the retailer's processes related to reverse logistics, such as shipment, categorization, and inventory replenishment.

Retailers can improve their warehouse procedures when the number of returns decreases. This may imply a reduction in the allocation of resources towards the review, classification, and management of products that have been returned. As a

result, this has the potential to improve the overall efficiency and quickness of warehouse activities. The literature also displays that implementation of return limitations can potentially mitigate costs associated with reverse logistics. Reduced quantities of returned products result in decreased expenditures on transportation, evaluation, restocking, and the possible refurbishment or disposal of said products. This has the potential to result in cost reductions for the apparel retailers.

The findings indicate that a strict return policy does not exert any significant impact on customers' inclination to return products. The results of the final exploratory factor analysis indicate that the items related to a strict return policy demonstrate loading on distinct factors or dimensions, thereby suggesting that the construct is characterized by multidimensionality. This implies that diverse elements of a strict return policy can have differential effects on customers' return behavior (Hair et al., 2019). The results obtained from the final exploratory factor analysis and path analysis suggest that the overall strictness of the return policy may not be the main determinant of customers' return behavior. Various factors such as product quality, price, customer satisfaction, and convenience of the return process, as well as previous return experience, may exert greater influence on customers' decisions to initiate returns (Dailey & Ülkü, 2018). The findings suggest that customers demonstrate a tendency to return products they have purchased, regardless of the level of strictness associated with the return policy. This indicates that the decision-making process of customers with regards to returns is influenced by a multitude of factors, and the strictness of the policy alone may not be the predominant determinant of their return behavior.

It is advisable to exercise caution while interpreting the outcomes pertaining to this variable since H2 is not fulfilled. It is noteworthy that the present study does not encompass data from industries such as apparel retailers or transportation and distribution service providers.

The result from the path analysis indicates a significant statistical association between the **Practices** variable and the **Return decision** variable, with a p-value of 0.076 (on a 10% level). This does not contradict with the findings in the literature, since researchers have found that returned apparel products are typically transported to the warehouse or to the manufacturer (Cricelli et al., 2021). This return method is known as reverse logistics, and many apparel retailers treat them

as a cost instead of an asset. The recognition of consumer returns as a significant aspect of apparel retailers' business is essential, particularly in the field of internet retailing. Internet retailers must acknowledge the considerable costs and consistent increase in return volumes associated with this matter (Hjort et al., 2019). In order to ensure effectiveness and efficiency, it is essential to define goals and strategy when implementing returns management. This plays an important role in achieving success. This could also display why this variable could explain the correlation on consumers return behavior.

The literature also suggests that implementing gatekeeping practices has allowed apparel retailers to effectively interact with customers who initiate returns. This has resulted in the establishment of standardized procedures that effectively prevent unwanted returns. This approach effectively mitigates the need for transportation and warehouse operations that are typically linked with the processing of returns. The level of gatekeeping utilized is frequently predicated on the observed return rates. In instances of elevated return rates, gatekeeping is generally confined to downstream procedures. In cases of low return rates, retailers may expand their gatekeeping practices to encompass downstream online channels (Hjort et al., 2019).

The multiple regression conducted in the path analysis aids the author to get insights into the size and trend of the relationship between each predictor and the response variable, while accounting for the influence of the remaining predictors. In the context of statistical analysis, multiple regression is a versatile modeling technique that has the capability to account for interaction effects. These interaction effects manifest when the influence of a particular predictor on the response variable is contingent upon the specific value of another predictor.

The impact of the return process's efficiency and ease on customers' decisions to initiate returns can be substantial. The findings explain that many apparel retailers practice a lenient policy where it is easy to return a product, several retailers have tried strategies like a keep reward being stricter with the leniency of their return policy (Ardeshirilajimi & Azadivar, 2015; Frei et al., 2020; Hjort et al., 2019). This indicates that apparel retailers' practices within their logistics are an important factor that can partly explain customers' return decision.

It is recommended to exercise prudence when interpreting the findings related to this variable, despite the fulfillment of H3. It is pertinent to note that the current investigation does not incorporate data from sectors such as apparel retailers or entities that offer conveyance and allocation services. The research is centered on the assessment of consumer perspectives within the Norwegian market.

The result from the path analysis displays that the variable **Return decision** was statistically significant on the variable **Performance**, with a p-value of 0.021 (on a 5% level). This is in accordance with the literature, apparel retailers online return practices do not only affect their everyday operations, but also consumers return decision. The researchers Zhi Pei and Audhesh Paswan found that there exist two different return behaviors, and these are legitimate return behaviors and opportunistic return behaviors (Pei & Paswan, 2018).

The concept of legitimate return behavior pertains to acceptable practices that are commonly observed in a mature market. These practices may involve the return of products due to defects in quality, errors committed by the seller, buyer's remorse, or changes in the external market (Pei & Paswan, 2018, p. 304). On the other hand, opportunistic return behavior can be characterized as a self-interested pursuit that is often accompanied by deceitful tactics. The concept of guile refers to the strategic use of deceitful or manipulative tactics in order to attain a desired outcome. This notion is particularly relevant within the context of supply chain management, where various stakeholders may employ guileful strategies in order to gain a competitive advantage or maximize their own interests (Pei & Paswan, 2018, p. 304).

The literature also highlights that consumers return decisions affects retailers' operation when it comes to inventory management, transportation, and reverse logistics. These activities affect apparel retailers' performance in terms of costs, which affects the bottom line (Gustafsson et al., 2021).

The results from the path analysis indicate a significant association between the variables of Return Decision and Performance. The finding suggests that consumer decisions regarding product returns have a significant impact on the overall performance of apparel retailers. The decisions made by consumers regarding returns have the potential to affect numerous aspects of retailers' performance,

including profitability, customer satisfaction, transportation costs, return costs, inventory holding costs, and product handling costs (Gustafsson et al., 2021; Pei & Paswan, 2018).

The study's results are consistent with the existing literature, thereby satisfying hypothesis H4. Even if H4 is fulfilled, please be aware that the present research does not contain information from sectors like apparel retailers or companies that offer transportation and distribution services.

6.2. Managerial implications

Since both a lenient return policy had a negative impact on consumers return decision, managers in apparel retailer companies should look at how their lenient return policy affects their inventory operations, reverse logistics, transportation costs (Gustafsson et al., 2021). By looking at these factors, managers could assess new criteria and guidelines for accepting returns. After this is done, they should see how these new guidelines and criteria have affected their logistical operations, inventory operations and bottom line (De Leeuw et al., 2016; Gustafsson et al., 2021).

The implementation of a strict return policy has facilitated the engagement of apparel retailers with customers who wish to return their purchased products, enabling the establishment of standardized protocols with the goal of mitigating the occurrence of undesirable returns. Consequently, this practice has resulted in a reduction in the demand for transportation and warehouse operations (Hjort et al., 2019). Since the findings show that strict return policy has a negative impact on consumers return decision, manager probably should implement less strict policies and see if this enhances customer satisfaction, customer loyalty and costs directed towards their logistics activities (Ahsan & Rahman, 2021; Bolton et al., 2000; Gustafsson et al., 2021). This can aid the manager to change the leniency of strictness of their return policy by looking at the cost development of the logistical activities.

Since the results implied that consumers return decision affects apparel retailers performance, managers in apparel retailer companies should focus on internal integration, so that the return processes, inventory processes and transportation processes can be furtherly improved. They could use the findings to make their

supply chain both upwards and downwards more cost efficient and more sustainable.

7. Conclusion

This research gives insight to which incentive influence consumers return decisions and how return decision influence apparel retailers' performance. This could come in handy when researchers or managers want to see what factors affect consumer returns and how returns affect retailers' performance. The findings of the research show partial conformity with the existing literature, as they indicate that two out of the four proposed hypotheses are fulfilled. As a result, influencing consumers return decision and apparel retailers performance is vast and highly complex. There could be other incentives than the ones I chose, that could influence consumers' return decision. The study shows that the significant predictor of return decision is the variable practices, while the significant predictor of performance is return decision.

Through the literature review the author gained better understanding to how return policies and practices are essential to determine apparel retailers' bottom line and consumers return behavior. Apparel retailers practices has a positive effect on consumers return decision and result in an enhanced customer satisfaction, stronger relationships with customers and reduced return rates (Gustafsson et al., 2021). Return decision had a positive effect on apparel retailers' performance and resulted in increased profitability and lessen the impact of product returns.

Apparel retailers should look at returns management as an essential component of their operations to optimize their management of product returns and performance. Through the implementation of sustainability-oriented and customer-centric approaches, retailers may encourage improvements in their overall operational procedures.

Overall, the research question was created to see how return policies and practices affect consumers online shopping behavior and apparel retailers' performance. To answer this research question, I conducted a factor analysis to see if any items should have been removed. A path analysis was also conducted to see which variable affected consumers return decision and if return decision affected

performance. The findings indicated that only practices affected return decision, while return decision had a significant effect on performance.

7.1. Further research and limitations

The limits of the study are described in this section of the thesis, along with potential directions for further investigation.

The first limitation in this study is that the respondents who answered the survey are to some extent biased, because they consisted of fellow students, acquaintances, friends, family members, family members work colleagues and the supervisor. For this reason, further research should include a much larger sample size of consumers located in different areas and cities around the country.

None of the variables are based on an established scale but based on inspiration from previous research papers and from the supervisor. The variable **SP** was the only variable that did not pass the benchmark of 0.5 in Cronbach's alpha. This could indicate that the items forming the variable Strict return policy are not dependably measuring the same underlying construct. When the Cronbach's alpha value falls below the established benchmark, it suggests that the items in the measurement instrument are not highly correlated with one another. This lack of correlation may indicate the presence of inconsistencies or weaknesses in the instrument's measurement capabilities. For this reason, further research should try to involve established scales or measures pertaining to related constructs in establishing both convergent and discriminant validity.

Since the author chose to focus on consumers opinion in the Norwegian market, further research should include data collection from Norwegian apparel retailers, transportation, and distribution service providers. Data collection from Norwegian apparel retailers, transportation, and distribution service providers could give significant insights into industry-specific practices, difficulties, and operational realities. Further research has the potential to generate a greater understanding of the supply chain used by Norwegian apparel retailers. This could improve the process of benchmarking and comparison, as well as improve the practical implications of resulting findings.

The author chose not to include a question, where respondents had to enter their postal code in terms of their geographical location. For this reason, further research

should include geographical location since it could reveal regional differences, cultural influences and buying behavior related to apparel products.

Lastly, this research was conducted in Norway, and related research conducted in other countries could obtain a different result. It could be very exciting to see if the results to the research question, based on the author's research model would be differ in other countries.

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8. Appendices

8.1. Appendix 1 – Questionnaire from a former master thesis

Table 1: Questionnaire items for Eco-design

Item	Item description	Source
Eco_1	Our company considers the recycling of packaging materials when choosing our packaging	Dong et al. (2019)
Eco_2	Our company minimizes the use of raw materials and energy in our packaging	Dong et al. (2019)
Eco_3	Our company's packaging has recycled materials in their contents	Hsu et al., (2013)
Eco_4	Our company's packaging materials are recyclable or reusable	Hsu et al., (2013)
Eco_5	Our company has removed all hazardous materials in our packaging	Jaaffar & Kaman, (2020)
Eco_6	Our company considers how easy materials in our packaging is to separate from each other	Lu & Xu, (2018)

Table 2: Questionnaire items for Regulations

Item	Item description	Source
Reg_1	Our company has made changes in our packaging to reduce or avoid a possible threat from environmental regulations	Hsu et al., (2013)
Reg_2	There are a large number of environmental regulations and restrictions on our firm's industry	Hsu et al., (2013)
Reg_3	There are frequent government inspections on our firm to ensure that we are in compliance with environmental laws	Hsu et al., (2013)
Reg_4	Regulations has greatly influenced our company's concern for environmental issues	Katsikeas et al, (2016)
Reg_5	Stricter environmental regulations are a major reason why our company is concerned about our impact on the environment	Katsikeas et al, (2016)
Reg_6	Our industry is faced with strict environmental regulations	Katsikeas et al, (2016)

Table 3: Questionnaire items for Customer demand

Item	Item description	Source
Cust_1	Our customers tend to buy environmentally friendly products	Dong et al. (2019)
Cust_2	Our customers will hold back on a purchase if we have not met their environmental requirement	Dong et al. (2019)
Cust_3	Our customers have a clear policy statement regarding their commitment to the environment	Hsu et al., (2013)
Cust_4	Our customers are increasingly demanding environmentally friendly products	Katsikeas et al, (2016)
Cust_5	Our customers expect our company to be environmentally friendly	Katsikeas et al, (2016)

Table 5: Questionnaire items for Recycling technology

Item	Item description	Source
Recycl_1	The quality of recycled material is sufficient enough for our company to use it	Rahmani et al, (2021)
Recycl_2	The access to recycled material is sufficient enough for our company to obtain what we want	Rahmani et al, (2021)

Table 4: Questionnaire items for Financial availability

Item	Item description	Source
Finan_1	Our company has easy access to financial capital to support its business operations	Memon et al, (2020)
Finan_2	Our company is better financed than our competitors	Memon et al, (2020)
Finan_3	If we need more financial assistance, we can easily obtain it (from for example loan or the government)	Memon et al, (2020)
Finan_4	Our company are able to obtain financial resources at short notice to support business operations	Memon et al, (2020)
Finan_5	Our company have adequate financial resources to choose environmentally friendly packaging	Memon et al, (2020)

Table 6: Questionnaire items for Information sharing

Item	Item description	Source
Info_1	The PRO guides our company in choosing the most environmentally friendly materials for our packaging	Micheaux & Aggeri, (2021)
Info_2	The PRO gives our company information of which materials that are recyclable	Micheaux & Aggeri, (2021)
Info_3	The PRO gives our company information of how environmentally friendly our packaging is	Micheaux & Aggeri, (2021)
Info_4	The PRO helps our company to assess how recyclable our packaging is	Micheaux & Aggeri, (2021)
Info_5	The PRO makes our company more aware of which circular initiatives our company can make when choosing our packaging	Micheaux & Aggeri, (2021)

Table 7: Questionnaire items for Fee modulation

Item	Item description	Source
FeeMod_1	increased the use of recycled materials in your packaging	Watkins et al, (2017)
FeeMod_2	consider recyclability when choosing packaging	Watkins et al, (2017)
FeeMod_3	had few different types of materials in the packaging	Watkins et al, (2017)
FeeMod_4	made the materials in the packaging even easier to separate	Watkins et al, (2017)
FeeMod_5	designed packaging to make it easier to sort and recycle (shape, labels, glues, inks, lids, etc.)	Watkins et al, (2017)

Table 8: Questionnaire items for Internal integration

Item	Item description	Source
Integ_1	Data integration among all internal functions	Flynn et al. (2010)
Integ_2	Our company has real-time operating data	Flynn et al. (2010)
Integ_3	Our company utilizes periodic meetings among internal functions	Flynn et al. (2010)
Integ_4	Our company use cross functional teams in process improvement	Flynn et al. (2010)
Integ_5	Our company use cross functional teams in new product development	Flynn et al. (2010)
Integ_6	Our company is integrated across the value chain (from raw materials to production, distribution, sales, and market)	Flynn et al. (2010)

8.2. Appendix 2 – Cover letter

Kjære alle sammen!

Denne undersøkelsen har til hensikt å kartlegge holdninger og praksis angående retur av varer når man kjøper klær/klesplagg på internett.

Undersøkelsen er relevant for alle personer i alle aldersgrupper.

Jeg er en masterstudent ved Handelshøyskolen BI som gjør denne studien for min avsluttende Masteroppgave. Jeg er avhengig av din hjelp for å få data som grunnlag for analysen. **Jeg håper at du kan sette av ca. 10-15 minutter ti å besvare spørreskjemaet som er vedlagt i denne linken.**

Link til spørreskjemaet: <https://nettskiema.no/a/336443>

Ditt svar vil være helt anonymt og det er frivillig å delta i studien. Innhentede data vil bli brukt til forskningsformål.

Jeg håper du vil bidra til kunnskap om denne spennende problemstillingen.

Jeg setter stor pris på om du også vil hjelpe meg å dele linken til spørreundersøkelsen med andre!

På forhånd hjertelig takk for hjelpen!

Vennlig hilsen

Glenn Runar Glesåen

Masterstudent ved Handelshøyskolen BI

8.3. Appendix 2 - Questions in Norwegian

Med fremveksten av internett gikk klesforhandlere over til det som nå er kjent som e-handel, netthandel eller internetthandel. I de siste årene har det vært et økende fokus på e-handel, netthandel og logistikk i klesbransjen. E-handel og netthandel har endret forbrukernes handlevaner og klesforhandlernes fremtid. Retur av produkter er et felt som har blitt mer omfattende og viktig. Produkter som returneres blir sjelden reparert eller får ny innpakning. Siden kundene kan returnere produktene sine, har e-handel økt mengden impulsive og kompulsive kleskjøp, samtidig som det har gjort det enklere å returnere dem. På grunn av dette har illegitim "låning" blitt mer akseptert i samfunnet.

Denne studien har til hensikt å undersøke hvordan klesforhandleres returordninger påvirker forbrukernes returvaner og praksis.

Etter noen innledende kategori spørsmål kommer det 5 hovedspørsmål angående returvaner og praksis.

Tabell 26: Spørreskjemaelementer for kategorisering av respondenter

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
Gender_1	What gender are you?	Hvilket kjønn er du?	Mann Dame Annet	(Wang et al., 2019)
Age_1	What is your age?	Hva er din alder?	18-25 26-35 36-45 46-55 56+	(Wang et al., 2019)
Education_1	What is your highest finished education?	Hva er din høyeste fullførte utdanning?	Videregående skole eller mindre Yrkesskole Bachelorgrad Mastergrad Doktorgrad(PhD)	(Wang et al., 2019)
Clothes_online_1	To what extent do you buy clothes online?	Hvor ofte kjøper du klær på nett?	I svært liten grad (1) I svært stor grad (5)	Selvlaget
Apparel_retailers_1	Can you name 3 clothing retailers from which you last bought clothes online?	Kan du nevne 3 klesforhandlere der du sist kjøpte klær på nettet?		Selvlaget

Spørsmål: I hvilken grad er du enig i de følgende uttalelsene når det gjelder dine handlevaner hos klesforhandlere på internett.

Jeg handler bare hos klesforhandlere på internett hvis:

Tabell 27: Spørsmål i spørreskjemaet for lempeligere returpolitikk

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
LP_1	The platform returns the goods in original price under any circumstances.	Klesforhandlere tar imot returnerte produkter til	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)

		samme pris som jeg betalte uten forbehold.		
LP_2	The platform permits a relatively long period for returning the commodities	Klesforhandlere tillater en relativt lang periode for retur av varer.	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)
LP_3	The platform takes charge of the shipping fee of returning the commodities under any circumstance	Klesforhandlere tar ansvaret for fraktgebyret når det gjelder retur av varer under alle omstendigheter.	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)
LP_4	The platform accepts the returns due to consumers' preferences or inconsistent expectations	Klesforhandlere godtar retur av varer dersom produktet ikke oppfyller mine forventninger.	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)
LP_5	Apparel retailers return service staff understand consumers' needs and requests for returns	Kundeservicemedarbeidere til klesforhandlere forstår mine ønske og behov når det gjelder retur av varer.	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)

Noen klesforhandlere har en strengere returpraksis ved kjøp av varer på internett.

I hvilken grad er du enig i følgende uttalelser:

Jeg handler hos klesforhandlere på internett med en strengere returpraksis hvis:

Tabell 28: Spørsmål i spørreskjemaet for streng returpolitikk

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
SP_1	Apparel retailers' gatekeeping practices are fair and reasonable	Klesforhandleres kontroll av returnerte varer blir praktiesert på en rettferdig og fornuftig måte.	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019, p. 774)

SP_2	Apparel retailers provide specific and clear return service explanations.	Klesforhandlere gir tydelige og klare forklaringer om deres returservice.	I svært liten grad (1) I svært stor grad (5)	(Wang et al., 2019, p. 39)
SP_3	I do not purchase apparel products online from a retailer that applies a strict return policy	Jeg kjøper ikke klesprodukter på nettet fra en forhandler som har strenge regler for retur?	I svært liten grad (1) I svært stor grad (5)	(Wang et al., 2019)
SP_4	Would you introduce or recommend an apparel retailer which applies a strict return policy to your friends	I hvilken grad ville du introdusert eller anbefalt en klesforhandler som benytter en streng retur praksis til en venn?	I svært liten grad (1) I svært stor grad (5)	(Wang et al., 2019)
SP_5	To what extent do you agree with clothing retailers that use strict return practices	I hvilken grad er du enig med klesforhandlere som benytter seg av en streng retur praksis?	Helt uenig (1) Helt enig (5)	(Wang et al., 2019)

Tabell 29: Spørsmål i spørreskjemaet for praksis

Klesforhandlere kan innføre ulik praksis for å hjelpe en kunde som handler på internett.

I hvilken grad er du enig i følgende uttalelser når det gjelder klesforhandleres praksis på internett:

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
Practices_1	Size guides and detailed product descriptions, can help consumers to make more informed decisions	Størrelsesguider og detaljerte produktbeskrivelser kan hjelpe forbrukere til å ta	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019)

		mer informerte beslutninger.		
Practices_2	I believe that organizations should have mandatory environmental care practices.	Jeg mener alle klesforhandlere bør innføre en bærekraftig praksis. (Forhandleren gjør en innsats for å redusere miljøpåvirkningen i produktets livssyklus)	I svært liten grad (1) I svært stor grad (5)	(Gomes De Oliveira et al., 2022)
Practices_3	Apparel retailer's customer services have a significant impact on consumers purchase decision	Klesforhandlernes kundeservice har en betydelig innvirkning på forbrukernes kjøpsbeslutning.	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019)
Practices_4	I would pay more for sustainable products	Jeg er villig til å betale mer for bærekraftige produkter.	I svært liten grad (1) I svært stor grad (5)	(Gomes De Oliveira et al., 2022)
Practices_5	Customers are more likely to purchase apparel products online if they know they can return it without a charge	Kunder er mer tilbøyelige til å kjøpe klesprodukter på internett hvis de vet at de kan returnere dem kostnadsfritt.	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019)

Tabell 30: Spørsmål i spørreskjemaet for vedtak om retur

I hvilken grad er du enig i følgende uttalelser når det gjelder beslutning om å kjøpe varer på internett?

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
RD_1	I know a lot about online stores' return policies	Jeg vet mye om klesforhandlernes returpraksis.	Helt uenig (1) Helt enig (5)	(Gelbrich et al., 2017, p. 867)

RD_2	It is very likely that I would order the item from this online store	Det er svært sannsynlig at jeg vil bestille klær fra en klesforhandlers nettbutikk.	Helt uenig (1) Helt enig (5)	(Gelbrich et al., 2017)
RD_3	I usually keep the products, I have bought online	Jeg beholder vanligvis produktene jeg har kjøpt på internett.	Helt uenig (1) Helt enig (5)	(Gelbrich et al., 2017)
RD_4	Have you ever decided not to make a purchase from a retailer because of their return policy	Har du noen gang bestemt deg for ikke å kjøpe fra en forhandler på grunn av returpolitikken deres?	Helt uenig (1) Helt enig (5)	(Gelbrich et al., 2017)
RD_5	The time window to return a product is crucial for me before I decide to make a purchase	Tidsvinduet for å returnere en vare er avgjørende for meg før jeg velger å foreta et kjøp.	Helt uenig (1) Helt enig (5)	(Yu & Kim, 2019)

Tabell 31: Elementer i spørreskjemaet for ytelse

I hvilken grad er du enig i følgende beskrivelser om klesforhandleres måte å drive forretning på?

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
Performance_1	I could observe that sustainable practices are widely publicized in the media	Jeg har observert at klesforhandleres bærekraftige praksis er mye omtalt i media.	I svært liten grad (1) I svært stor grad (5)	(Gomes De Oliveira et al., 2022)
Performance_2	Consumers are more likely to return a product if the quality of the product is poor	Forbrukere kommer mest sannsynlig til å returnere et produkt hvis kvaliteten på produktet er lavt.	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019)
Performance_3	Retailers' product and service development is based on customer-focused information	Klesforhandlerens produkt- og tjenesteutvikling er basert på kundens behov.	I svært liten grad (1) I svært stor grad (5)	(Jack et al., 2010)

Performance_4	Apparel retailers can improve their performance by looking at customers' feedback	Klesforhandlere kan gjøre forbedringer ved å følge opp kundenes tilbakemeldinger.	I svært liten grad (1) I svært stor grad (5)	(Hjort et al., 2019)
Performance_5_1	I believe that online apparel retailers get more product returns than traditional clothing retailers with physical stores	Jeg tror at klesforhandlere på internett får flere produktreturer enn klesforhandlere med fysiske butikker	I svært liten grad (1) I svært stor grad (5)	(Griffis et al., 2012)
Performance_5_2	I believe that online clothing retailers have higher costs in processing returns compared to physical stores	Jeg tror at klesforhandlere på internett har høyere kostnader ved å behandle retur sammenlignet med fysiske butikker	I svært liten grad (1) I svært stor grad (5)	(Griffis et al., 2012)

Tabell 32: Kundetilfredshet

Artikkel	Spørsmål på engelsk	Spørsmål på norsk	Valgmulighet	Kilde
Satisfaction_1	To what extent are you satisfied with clothing retailers' online return schemes	I hvilken grad er du fornøyd med klesforhandlernes returordninger på internett?	Lite fornøyd (1) Svært fornøyd (5)	Selvlaget
Satisfaction_2	To what extent will you continue to buy clothes online	I hvilken grad vil du fortsette å kjøpe klær på internett?	I svært liten grad (1) I svært stor grad (8)	Selvlaget

8.4. Appendix 3 – Descriptive Statistics of Variable Items

The author starts with the independent variables *Lenient return policy*, *Strict return policy* and *Practices*. These independent variables are inspired from different research papers and supervisor Bente Merete Flygansvær. Next are the dependent variables *Return decision* and *Performance*. The variable *Return decision* is intended to capture consumers return decision based on apparel retailers' practices and their return policy. The *Performance* variable is intended to capture apparel retailers' performance based on consumers return decision. These two dependent variables are based on inspiration from different research papers.

8.4.1. *Lenient return policy*

The frequencies from the variable **LP** (Lenient return policy) shows that level of a lenient return policy is high among the respondents. It is quite clear that 36.89% of the respondents strongly agree with this statement “The platform returns the goods in original price under any circumstances” (**LP_1**), whereas 18.45% somewhat agree. LP_1 has a mean value of 3.92, which signifies a high level of agreement. Only 14.56% strongly agree with the statement “The platform permits a relatively long period for returning the commodities” (**LP_2**), whereas 30.10% somewhat agree, and 40.78% agreed. LP_2 has a mean of 3.51, which signifies a high level of agreement. 25.24% strongly agree with the statement “The platform takes charge of the shipping fee of returning the commodities under any circumstance” (**LP_3**), whereas 22.33% somewhat agree. LP_3 has a mean value of 3.56, which signifies a high level of agreement. 43.69% strongly agree with this statement “The platform accepts the returns due to consumers' preferences or inconsistent expectations” (**LP_4**), whereas only 12.62% somewhat agree. LP_4 has a mean value of 4.13 which signifies a very high level of agreement. 40.78% agree with this statement “Apparel retailers return service staff understand consumers' needs and requests for returns” (**LP_5**), whereas 24.27% somewhat agree. LP_5 has a mean value of 3.79 which signifies a high level of agreement. In conclusion, this variable indicates a high level of Lenient return policy among the respondents.

LP_1	Frequency	Percent	Mean
5 (Strongly agree)	38	36.89%	3.92
4 (Agree)	36	34.95%	
3 (Neither / nor)	19	18.45%	
2 (Disagree)	6	5.83%	
1 (Strongly disagree)	5	4.85%	
LP_2	Frequency	Percent	Mean
5 (Strongly agree)	15	14.56%	3.51
4 (Agree)	42	40.78%	
3 (Neither / nor)	31	30.10%	
2 (Disagree)	13	12.62%	
1 (Strongly disagree)	3	2.91%	
LP_3	Frequency	Percent	Mean
5 (Strongly agree)	26	25.24%	3.56
4 (Agree)	34	33.01%	
3 (Neither / nor)	23	22.33%	
2 (Disagree)	14	13.59%	
1 (Strongly disagree)	7	6.80%	
LP_4	Frequency	Percent	Mean
5 (Strongly agree)	45	43.69%	4.13
4 (Agree)	39	37.86%	
3 (Neither / nor)	13	12.62%	
2 (Disagree)	3	2.91%	
1 (Strongly disagree)	4	3.88%	
LP_5	Frequency	Percent	Mean
5 (Strongly agree)	26	25.24%	3.79
4 (Agree)	42	40.78%	
3 (Neither / nor)	25	24.27%	
2 (Disagree)	7	6.80%	
1 (Strongly disagree)	3	2.91%	

Table 33: Frequency of items from the variable Lenient return policy

8.4.2. *Strict return policy*

The frequency analysis of the variable **SP** (Strict return policy) shows that a significant number of respondents prefer a low level of strict return policy. From the table below, it is very clear that 39.81% of the respondents agree with this statement “Apparel retailers’ gatekeeping practices are fair and reasonable” (**SP_1**), whereas 34.95% somewhat agree. **SP_1** has a mean value of 3.66, which signifies a high level of agreement. 28.54% agree with this statement “I do not purchase apparel products online from a retailer that applies a strict return policy” (**SP_2**), whereas only 7.77% of the respondents disagree. **SP_2** has a mean value

of 3.83 which signifies a high level of agreement. Only 16.5% of the respondents strongly agree with this statement “Would you introduce or recommend an apparel retailer which applies a strict return policy to your friends” (SP_3), while 39.81% of the respondents somewhat agree. SP_3 has a mean value of 3.27 which signifies an average level of agreement. 33.98% of the respondents answered to a low degree on this statement “Would you introduce or recommend an apparel retailer which applies a strict return policy to your friends” (SP_4), while 32.04% of the respondents answered to some degree. This indicates that very few of the respondents would introduce an apparel retailer to their friends, that has strict return practices. SP_4 has a mean value of 2.21 which signifies that most respondents do not agree with this statement. Only 1.94% strongly agree with this statement “To what extent do you agree with clothing retailers that use strict return practices” (SP_5), while 32.04% disagree with this statement. SP_5 has a mean value of 2.32 which signifies a low level of agreement.

This variable indicates that most of the respondents are not particularly satisfied with apparel retailers that practice a strict return policy.

SP_1	Frequency	Percent	Mean
5 (Strongly agree)	19	18.45%	3.66
4 (Agree)	41	39.81%	
3 (Neither / nor)	36	34.95%	
2 (Disagree)	6	5.83%	
1 (Strongly disagree)	2	1.94%	
SP_2	Frequency	Percent	Mean
5 (Strongly agree)	25	24.27%	3.83
4 (Agree)	50	48.54%	
3 (Neither / nor)	18	17.48%	
2 (Disagree)	8	7.77%	
1 (Strongly disagree)	3	2.91%	
SP_3	Frequency	Percent	Mean
5 (Strongly agree)	17	16.50%	3.27
4 (Agree)	23	22.33%	
3 (Neither / nor)	41	39.81%	
2 (Disagree)	17	16.50%	
1 (Strongly disagree)	6	5.83%	
SP_4	Frequency	Percent	Mean
5 (Very large extent)	1	0.97%	2.21
4 (Large extent)	7	6.80%	
3 (To some extent)	33	32.04%	
2 (Low extent)	35	33.98%	
1 (Very low extent)	28	27.18%	
SP_5	Frequency	Percent	Mean
5 (Strongly agree)	2	1.94%	2.32
4 (Agree)	10	9.71%	
3 (Neither / nor)	33	32.04%	
2 (Disagree)	33	32.04%	
1 (Strongly disagree)	26	25.24%	

Table 34: Frequency of items from the variable Strict return policy

8.4.3. *Practices*

Table 28 on the next page, shows that 45.63% agree with the statement “Size guides and detailed product descriptions can help consumers to make more informed decisions” (**Practices_1**), whereas only 10.68% stand neutral. Practices_1 has a mean value of 4.23, which signifies a high level of agreement. 44.66% agree with this statement “I believe that organizations should have mandatory environmental care practices” (**Practices_2**), whereas 29.13% somewhat agree. Practices_2 has a mean value of 3.78 which signifies a high level of agreement. 49.51% agree with this statement “Apparel retailer’s customer services have a significant impact on consumers purchase decision” (**Practices_3**), whereas 20.39% are neutral to this agreement. Practices_3 has a mean value of 3.78 which signifies a high level of agreement amongst the respondents. Only 4.85% strongly agree with this statement “Apparel retailers can improve their performance by looking at customers’ feedback” (**Practices_4**), whereas 30.10% somewhat agree with this statement. Practices_4 has a mean value of 2.90 which signifies that most respondents do not agree with this statement. 54.37% of the respondents agree with this statement “I believe that online retailers see a higher level of product returns than conventional retailers and that the cost of processing these returns is higher” (**Practices_5**), whereas only 6.80% of the respondents somewhat agree. Practices_5 has a mean value of 4.37 which signifies a very high agreement.

The author would like to conclude that the overall mean value of 3.81 from the different items shows that most respondents support apparel retailers’ practices.

Practices_1	Frequency	Percent	Mean
5 (Strongly agree)	47	45.63%	4.23
4 (Agree)	41	39.81%	
3 (Neither / nor)	11	10.68%	
2 (Disagree)	3	2.91%	
1 (Strongly disagree)	2	1.94%	
Practices_2	Frequency	Percent	Mean
5 (Strongly agree)	22	21.36%	3.78
4 (Agree)	46	44.66%	
3 (Neither / nor)	30	29.13%	
2 (Disagree)	3	2.91%	
1 (Strongly disagree)	3	2.91%	
Practices_3	Frequency	Percent	Mean
5 (Strongly agree)	22	21.36%	3.78
4 (Agree)	51	49.51%	
3 (Neither / nor)	21	20.39%	
2 (Disagree)	6	5.83%	
1 (Strongly disagree)	4	3.88%	
Practices_4	Frequency	Percent	Mean
5 (Strongly agree)	5	4.85%	2.90
4 (Agree)	32	31.07%	
3 (Neither / nor)	31	30.10%	
2 (Disagree)	20	19.42%	
1 (Strongly disagree)	16	15.53%	
Practices_5	Frequency	Percent	Mean
5 (Strongly agree)	56	54.37%	4.37
4 (Agree)	37	35.92%	
3 (Neither / nor)	7	6.80%	
2 (Disagree)	1	0.97%	
1 (Strongly disagree)	3	2.91%	

Table 35: Frequency of items from the variable Practices

8.4.4. *RD (Return decision)*

Return decision is the dependent variable that catches consumers return decisions based on apparel retailers’ practices and return policy. Only 3.88% of the respondents strongly agreed with this statement “I know a lot about online stores’ return policies” (**RD_1**), while 38.33% answered to some extent and 22.33% answered to a low extent. This indicates that most of the respondents do not check apparel retailers return policy before they purchase clothes online. RD_1 has a mean value of 2.95, which signifies that most of the respondents do not check apparel retailers return policy. When it comes to the item **RD_2** 35.92% of the respondents agreed to a large extent with this statement “It is very likely that I would order the item from this online store”, while 31.07% agreed to some extent,

10.68% to a low extent and 4.85% to very low extent. RD_2 has a mean value of 3.52, which indicates that most of the respondents agree with this statement. The item **RD_3** had this statement “I usually keep the products, I have bought online”, whereas 51.46% responded to a large extent, and only 0.97% responded to a low extent. RD_3 has a mean value of 4.04, and this signifies that most of the respondents keep the apparel products they have purchased online. Regarding **RD_4** statement “Have you ever decided not to make a purchase from a retailer because of their return policy”, 25.24% of the respondents answered to a very low extent. The item RD_4 has a mean value of 2.66, which is low. This could indicate that most of the respondents do not take apparel retailers return policy into account when purchasing clothes online. From the table on the next page, it is quite clear that 36.89% agree to some extent on this statement “The time window to return a product is crucial for me before I decide to make a purchase” (**RD_5**), while 21.36% of the respondents answered to a very low extent.

In conclusion, the variable Return decision indicates that the majority of respondents retain the online-purchased apparel products.

RD_1	Frequency	Percent	Mean
5 (Very large extent)	4	3.88%	2.95
4 (Large extent)	28	27.18%	
3 (To some extent)	40	38.83%	
2 (Low extent)	23	22.33%	
1 (Very low extent)	9	8.74%	
RD_2	Frequency	Percent	Mean
5 (Very large extent)	19	18.45%	3.52
4 (Large extent)	37	35.92%	
3 (To some extent)	32	31.07%	
2 (Low extent)	11	10.68%	
1 (Very low extent)	5	4.85%	
RD_3	Frequency	Percent	Mean
5 (Very large extent)	29	28.16%	4.04
4 (Large extent)	53	51.46%	
3 (To some extent)	20	19.42%	
2 (Low extent)	1	0.97%	
1 (Very low extent)	1	0.97%	
RD_4	Frequency	Percent	Mean
5 (Very large extent)	10	9.71%	2.66
4 (Large extent)	20	19.42%	
3 (To some extent)	25	24.27%	
2 (Low extent)	23	22.33%	
1 (Very low extent)	26	25.24%	
RD_5	Frequency	Percent	Mean
5 (Very large extent)	4	3.88%	2.60
4 (Large extent)	17	16.50%	
3 (To some extent)	38	36.89%	
2 (Low extent)	23	22.33%	
1 (Very low extent)	22	21.36%	

Table 36: Frequency of items from the variable Return decision

8.4.5. *Performance*

Table 30 shows that 3.88% of the respondents agreed to a very large extent, while only 12.62% agreed to a large extent with the statement “I could observe that sustainable practices are widely publicized in the media” (**Performance_1**). Overall, over half (47.57%) of respondents indicated some level of agreement with the statement. Performance_1 has a mean value of 2.75 which signifies that most of the respondents do not agree to a large extent. For the statement “Consumers are more likely to return a product if the quality of the product is poor” (**Performance_2**), where only 19.42% of the respondents agreed to a very large extent, while 39.81% agreed to a large extent. 35.92% agreed to some extent with the statement. Performance_2 has a mean value of 3.71 which signifies a high level of agreement. When it comes to the third item statement “Retailers’ product and service development is based on customer-focused information” (**Performance_3**), most respondents agreed to some extent (47.57%), while only 5.83% agreed to a very large extent. Performance_3 had a mean value of 3.38, which signifies that most respondents do not agree with this statement. Regarding the statement of the fourth item in the variable performance “Apparel retailers can improve their performance by looking at customers’ feedback” (**Performance_4**), only 20.39% agreed to a very large extent, while most of the respondents agreed to a large extent, with a percentage of 50.49%. The item performance_4 has a mean value of 3.90, which signifies that most of the respondents agree with the statement. 38.83% of the respondents agreed to a large extent regarding this statement “I believe that online apparel retailers get more product returns than traditional clothing retailers with physical stores” (**Performance_5_1**), whereas 28.16% agreed to some extent with the statement. The mean value of 3.81 indicates that most of the respondents agreed with this statement. Regarding the last item’s statement “I believe that online clothing retailers have higher costs in processing returns compared to physical stores” where most of the respondents (38.83%) agreed to a large extent, while only 9.71% of the respondents agreed to a low extent. The item’s mean value of 3.54 indicated that most of the respondents agreed with this statement.

Performance_1	Frequency	Percent	Mean
5 (Very large extent)	4	3.88%	2.75
4 (Large extent)	13	12.62%	
3 (To some extent)	49	47.57%	
2 (Low extent)	29	28.16%	
1 (Very low extent)	9	8.74%	
Performance_2	Frequency	Percent	Mean
5 (Very large extent)	20	19.42%	3.71
4 (Large extent)	41	39.81%	
3 (To some extent)	37	35.92%	
2 (Low extent)	5	4.85%	
1 (Very low extent)	1	0.97%	
Performance_3	Frequency	Percent	Mean
5 (Very large extent)	6	5.83%	3.38
4 (Large extent)	38	36.89%	
3 (To some extent)	49	47.57%	
2 (Low extent)	11	10.68%	
1 (Very low extent)	0	0.00%	
Performance_4	Frequency	Percent	Mean
5 (Very large extent)	21	20.39%	3.90
4 (Large extent)	52	50.49%	
3 (To some extent)	31	30.10%	
2 (Low extent)	0	0.00%	
1 (Very low extent)	0	0.00%	
Performance_5_1	Frequency	Percent	Mean
5 (Very large extent)	27	26.21%	3.81
4 (Large extent)	40	38.83%	
3 (To some extent)	29	28.16%	
2 (Low extent)	6	5.83%	
1 (Very low extent)	2	1.94%	
Performance_5_2	Frequency	Percent	Mean
5 (Very large extent)	15	14.56%	3.54
4 (Large extent)	40	38.83%	
3 (To some extent)	37	35.92%	
2 (Low extent)	10	9.71%	
1 (Very low extent)	2	1.94%	

Table 37: Frequency of items from the variable Performance

8.5. Appendix 4 - Methodology for multiple regression and path analysis

Code for counting educational background:

```
Survey_for_RStudio$Education <-
factor(Survey_for_RStudio$Highest_finished_education,
       levels = c(1, 2, 3, 4, 5),
```

```
labels = c("High School or Lower", "Technical School",
           "Bachelor Degree", "Master Degree",
           "Doctoral Degree (PHD)"))
```

```
education_counts <- table(Survey_for_RStudio$Education)
```

```
print(education_counts)
```

Output from RStudio:

```
High School or Lower    Technical School    Bachelor Degree    Master Degree    Doctoral Degree (PHD)
                28                12                37                25                1
```

Code for checking if age group or educational background is statistically significant with buying clothes online:

```
model <- lm(Buying_clothes_online_degree ~ age_group + Education, data =
Survey_for_RStudio)
```

```
summary(model)
```

Output from RStudio:

```
Residuals:
    Min       1Q   Median       3Q      Max
-1.71551 -0.71437  0.08945  0.54139  2.56974

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      2.00000    1.10519   1.810  0.0737
age_group20-29   0.71437    1.13353   0.630  0.5301
age_group30-39   0.93885    1.21075   0.775  0.4401
age_group40-49   1.94336    1.21309   1.602  0.1126
age_group50-59   0.51176    1.13656   0.450  0.6536
age_group60-69   0.30917    1.22108   0.253  0.8007
age_group70-79   0.74832    1.25278   0.597  0.5518
age_group80 and above -1.00000    1.56297  -0.640  0.5239
EducationTechnical School -0.08149    0.39884  -0.204  0.8386
EducationBachelor Degree -0.03281    0.28846  -0.114  0.9097
EducationMaster Degree -0.48024    0.31602  -1.520  0.1321
EducationDoctoral Degree (PHD) -0.51176    1.13656  -0.450  0.6536
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.105 on 91 degrees of freedom
Multiple R-squared:  0.142,    Adjusted R-squared:  0.03833
F-statistic: 1.37 on 11 and 91 DF, p-value: 0.2009
```

Creating a common variable for LP (Lenient return policy):

```
Survey_for_RStudio$LP <- rowMeans(Survey_for_RStudio[,c("LP_1", "LP_2",
"LP_3", "LP_4", "LP_5")], na.rm = TRUE)
```

```
summary(Survey_for_RStudio$LP)
```

Output from RStudio:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	3.400	4.000	3.777	4.200	5.000

Creating a common variable for SP (Strict return policy):

```
Survey_for_RStudio$SP <- rowMeans(Survey_for_RStudio[,c("SP_1", "SP_2",
"SP_3", "Strict_return_policy_introduce_retailer",
"Agree_with_retailer_strict_policy")], na.rm = TRUE)
```

```
summary(Survey_for_RStudio$SP)
```

Output from RStudio:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.000	2.800	3.200	3.054	3.400	4.000

Creating a common variable for Practices:

```
Survey_for_RStudio$Practices <-
rowMeans(Survey_for_RStudio[,c("Practices_1", "Practices_2", "Practices_3",
"Practices_4", "Practices_5")], na.rm = TRUE)
```

```
summary(Survey_for_RStudio$Practices)
```

Output from RStudio:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.400	3.600	4.000	3.812	4.200	4.800

Creating a common variable for RD (Return decision):

```
Survey_for_RStudio$RD <- rowMeans(Survey_for_RStudio[,c("RD_1", "RD_2",
"RD_3", "RD_4", "RD_5")], na.rm = TRUE)
```

```
summary(Survey_for_RStudio$RD)
```

Output from RStudio:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
1.00	2.80	3.20	3.15	3.60	4.40

Creating a common variable for Performance:

```
Survey_for_RStudio$Performance <-
rowMeans(Survey_for_RStudio[,c("Performance_1", "Performance_2",
"Performance_3", "Performance_4", "Performance_5_1", "Performance_5_2")],
na.rm = TRUE)
```

```
summary(Survey_for_RStudio$Performance)
```

Output from RStudio:

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2.333	3.167	3.500	3.516	3.833	4.833

Creating path analysis to check statistical significance:

```
model <- 'Performance ~ RD
         RD ~ LP + SP + Practices'
fit <- sem(model, data=Survey_for_RStudio)
fit
summary(fit)
```

Output from RStudio:

```
lavaan 0.6.15 ended normally after 1 iteration

Estimator ML
Optimization method NLMINB
Number of model parameters 6

Number of observations 103

Model Test User Model:

Test statistic 8.931
Degrees of freedom 3
P-value (Chi-square) 0.030

Parameter Estimates:

Standard errors Standard
Information Expected
Information saturated (h1) model Structured

Regressions:
      Estimate Std.Err z-value P(>|z|)
Performance ~
  RD          0.157   0.068   2.302   0.021
RD ~
  LP          0.128   0.090   1.418   0.156
  SP          0.027   0.131   0.207   0.836
  Practices   0.222   0.125   1.777   0.076

Variances:
      Estimate Std.Err z-value P(>|z|)
.Performance  0.207   0.029   7.176   0.000
.RD           0.382   0.053   7.176   0.000
```