UNIVERSITY OF SOUTHAMPTON

Faculty of Social Science

School of Mathematical Sciences

Explore the factors affecting the increase in returns of fashion products during the epidemic

by

[redacted]

This Dissertation is submitted in part-fulfilment of the requirements for the degree of Msc Data and Decision Analytics

09, 2022

Student Number: 33323607

ABSTRACT

The popularity of COVID-19 has hit fashion retailers hard, with total retail sales rising less while returns are increasing. To help fashion retailers reduce the incidence of return behaviour, this study used second hand survey data, first looked at customers' attitudes towards fashion returns and the characteristics of return behaviour from the customers' perspective, and found that the most important reason for customers' returns was uncertainty about the clothing product, especially uncertainty about clothing sizes. Factors were then extracted using exploratory factor analysis, and the three main factors that influenced the increase in the number of fashion returns by customers during the pandemic were lenient return policies, extra willingness to buy and perceived risk. Finally, some recommendations are given to fashion retailers to reduce the return rate based on the results of the analysis.

Key word: **COVID-19, PRODUCT RETURN, FASHION RETAILER**

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Acknowledgements

My story with Southampton started from the summer of 2021 and ended in the autumn of 2022. How time flies. If all goes well, my student status will end in November or December this year, as I will then receive my taught postgraduate diploma and officially start my working life. I sincerely hope I can have a happy ending .

But whether I graduate on time or not, I would like to express my most sincere gratitude to my two supervisors, Dr. Steffen and Dr. Regina, for their help and guidance during the completion of my dissertation. I would also like to thank the University of Southampton for providing us with a safe, comfortable learning environment so that I can successfully complete our postgraduate courses; and thank all the lecturers who have taught me for their hard work and dedication; and thank all my friends I have made in Southampton since they have brightened up my humdrum life and I hope to keep in touch with them in the future; and thank my parents creating the best conditions for me, without their encouragement understanding and endless love, I would not have been able to study abroad; thank my en-suite room, for giving me endless sense of security even though it was only a tiny room with a dozen square metres. Last but not least, I am deeply grateful to myself for never giving up and persevering to the end.

All in all, I wouldn't have made it this far without anyone. Thanks for having you and thanks for for having me. There seems to be a lot of regrets and things I haven't done in that year, but a life without regrets is not a life. This year of life will always be treasured by me.

Chapter 1 Introduction

1.1 Background

The sudden COVID-19 pandemic has taken the world by surprise. Lockdowns in some nations have made it difficult for people to travel, economies have slowed, total retail sales have dropped, and traditional brick-and-mortar stores have been particularly severely hit. The e-commerce sector is growing rapidly at a time when the overall situation is in tatters. In the EU-27, while total retail sales fell by 17.9% in April 2020 compared to April 2019, mail-order and online retail sales climbed by 30% (OECD, 2020). While online sales are growing, the the cost of returns to retailers cannot be ignored. A survey by Appriss and the National Retail Federation (NRF) reported that returns cost US retailers more than $761 billion in lost sales in 2021, an average of 16.6% of total retail sales, and that online returns accounted for an average of 20.8% of online sales, with returns in the apparel category were as high as 12.2% (Appriss, 2022). Demand for fashion products is decreasing as people's demand is mainly focused on daily necessities (Dowsett, 2020). The well-known online fast fashion retailer ASOS has seen an increase in sales but also a significant increase in returns, as it offers free returns. After earning more than £194 million in profit in 2021, ASOS is predicting a surprisingly low profit of between £20 million and £60 million this year (Kollewe and Makortoff, 2022).

From a merchant's point of view, product returns have always been one of the main issues that lead to reduced profits for businesses, both for online retailers and traditional brick-and-mortar shops. But in e-commerce sector, the physical distance between the customer and the retailer makes it more difficult for customers to identify products and the risk of shopping, especially for clothing items where people cannot try them on offline in a physical shop, so uncertainty about the size of the garment, the material and quality of the item often leads to product returns. For example, a customer may buy the same style of trousers in one go but in different sizes, then keep one in the right size and return it in another size.

In order to increase customers' willingness to buy, retailers have made a lot of effort. They are looking to investigate the factors that influence product returns in order to target them. The study identified product uncertainty, dissonance, retailer service failures, perceptions and opportunism as notable causes of fashion product returns. (Kaushik *et al.*, 2022). Moreover, in Lysenko-Ryba and Zimon's (2021) study, nearly half of respondents said they would not buy from the seller again after a failed return, which illustrates the importance customers place on the returns experience and that a poor returns experience can lead to customers moving away from that retailer. In order to increase sales, retailers are therefore relaxing their return policies and trying to make customers happy with their returns, reducing their perceived risk and increasing their willingness to buy and to repurchase.

However, by relaxing the consumer policy, sales increase and so do returns, with a negative impact on both the retailer and the environment. On the one hand, product returns can be detrimental to the interests of retailers. Retailers have to bear the costs of returning goods and handling secondary merchandise. Companies adding workers, increasing warehouse space and creating separate departments to deal with reverse logistics are all manifestations of the increased costs. On the other hand, the greenhouse gases emitted by reverse logistics and the packaging waste generated during the process put a lot of pressure on the environment.

It is therefore particularly important to find ways to reduce returns. This study investigates the factors affecting the increase in returns of consumer fashion items during COVID-19, uncovers the characteristics of customers' return behaviour and provides online merchants with recommendations to reduce the rate of customer returns, thereby reducing the costs consumed by retailers on returns and increasing profits, while contributing to the sustainable development of e-commerce.

1.2 Research Questions and Objectives

1.2.1 Research Questions

Explore how do people experience returns and what are their attitudes towards reducing returns and what factors influenced the increase in returns of fashion products during the pandemic. What recommendation can be given to fashion retailers on reducing return rates?

1.2.2 Research Objectives

The first objective is to discover what reasons or circumstances would make them return less from the customer's perspective during the pandemic; the second is to discover the factors that influence customer returns from the merchant's perspective.

1.3 Structure of the Dissertation

The introduction, literature review, methodology, analysis and results, discussion and conclusion are the six chapters that make up the entire dissertation. The introduction focuses on the dilemma of online fashion retailers in the age of pandemics, and introduces the questions and objectives of this study by describing the losses to retailers and the pressure on the environment caused by returns, prompting concern about fashion product returns and exploring the factors or conditions that influence fashion product returns.

The literature review begins with an introduction to the impact of the COVID-19 pandemic on consumers and fashion retailers, followed by a description of the factors that influence product returns, the negative impact of product returns, and a model for predicting product returns, respectively, culminating in explicit hypotheses on the impact of lenient return policies, additional purchase intentions and perceived risk, and finally concluding with the gaps in this study.

The methodology is based on the research onion and presents in sequence the research philosophy, approach, method, strategies used in this study, as well as the statistical methods and models used in the subsequent data analysis, one by one, and concludes with a statement of ethical issues.

The analysis and results started with a descriptive analysis showing the respondents' demographic information and experiences, perceptions and attitudes towards product returns, then after passing the reliability test, an exploratory factor analysis was conducted and finally the three factors obtained by dimensionality reduction were brought into the logistic regression equation and significant results were obtained.

The discussion compares and reflects on the results of the analysis with the literature in the literature review.

The conclusion summarises the content of the first five chapters and presents some of the limitations of the study, as well as an outlook for the future.

Chapter 2 Literature Review

2.1 Chapter Overview

The cost of returns to retailers cannot be ignored. After reading the extensive literature, this chapter first presents the impact of the COVID-19 pandemic on consumers and fashion retailers, then presents three aspects of product returns: three important factors affecting product returns, the negative consequences of product returns for retailers and the environment, and a model for predicting product returns, ultimately giving a clear picture of the impact of lenient return policies, additional willingness to buy and perceived risk are all hypothesised and conclude with the gap of this study.

2.2 Impact of COVID-19 Pandemic and Fashion Retailers

The lockdown and social distance imposed in response to the COVID-19 pandemic forced people to go out less. Eight direct effects of pandemics on consumption and consumer behaviour are listed by Sheth (2020), and they are as follows: "Hoarding, Improvisation, Pent-up Demand, Embracing Digital Technology, Store Comes Home, Blurring of Work-Life Boundaries, Reunions with Friends and Family and Discovery of Talent". According to Goswami and Chouhan's (2021) empirical study, there is a positive correlation between consumer behaviour and modifications in buying methods during the COVID-19 epidemic. The pandemic has accelerated the process of integrating physical shops with online shopping for some retailers, prompting the formation of omnichannel delivery (Sheth, 2020).

Some fashion retailers had temporarily closed their physical shops and switched to online sales (Brydges and Hanlon, 2020). People's purchasing power and demand for non-essential items like fashion products have decreased. The data show that while garment sales in Britain declined by 50% compared to an already-squeezed March, they fell by 89% in the United States in April compared to the same month in 2019 (Dowsett, 2020).

2.3 Product Returns

When choosing a product in a brick-and-mortar shops, product attributes can be typically visible and perceived. However, in online shopping, time lags and distance gaps prevent customers from being able to touch and experience the goods, and the presence of uncertainty leads to information asymmetry between buyers and sellers (Mavlanova, Benbunan-Fich and Koufaris, 2012), which trigger product return behaviour.

2.3.1 Factors Affecting Return

The literature and research on the causes and the variables influencing product returns have exploded in recent years. Product uncertainty, cognitive dissonance, and opportunistic returns were identified as common causes of product returns. Product uncertainty is considered a serious barrier in the e-commerce sector and the most intuitive and critical factor affecting consumers' willingness to return products, defined as the challenge for consumers in evaluating products and predicting their future performance, where both descriptive uncertainty and performance uncertainty are embedded (Dimoka, Hong and Pavlou, 2012). But in subsequent studies, product uncertainty was divided into two dimensions: fit uncertainty and quality uncertainty, and the former had a significantly greater impact on product returns than the latter (Hong and Pavlou, 2014). In the apparel industry, product fit uncertainty means that the size, colour, style, thickness, texture, stretchability, fabric or any other attributes of the garment may not match the customer's expectations (Kim and Damhorst, 2013), and some customers may order selections to reduce perceived risk but increase the likelihood of returns. Of the garment attributes, size variation is the most critical factor in garment returns (Kim and Damhorst, 2013; Kaushik *et al.*, 2022). In response to such issues, apparel retailers are working to improve the level of online interaction with users through digital technology (Blázquez, 2014), enhancing telepresence to alleviate the concerns of online shoppers regarding performance risks, reducing product return rate and creating an immersive shopping experience (Lim and Ayyagari, 2018). For instance, In e-shopping platforms, identical size charts by the same brand for the same type of clothing, multi-angle photos of item details, emerging virtual fitting rooms (Moroz, 2019) , and reviews of purchased items by other consumers (Wang, Ramachandran and Liu Sheng, 2021) are practical applications of telepresence in the cognitive, emotional, behavioural and collaborative dimensions of retailers (Lim and Ayyagari, 2018).

Cognitive dissonance is considered to be the underlying factor of product returns (Powers and Jack, 2013). Discomfort, anxiety, and/or regret brought on by conflicting cognitive elements after a purchase choice is completed are all considered symptoms of post-purchase disorder (Lee, 2015). Product dissonance and emotional dissonance, two forms of cognitive dissonance, have been proved to be positively correlated with the frequency of returns (Powers and Jack, 2013), with emotional dissonance having a significant impact on the two return factors of not meeting expectations and discovering a better product or price (Powers and Jack, 2015). The study of Powers and Jack (2015) also demonstrated that there was a positive relationship between product dissonance and emotional dissonance. Cognitive dissonance is also influenced by other factors while affecting product returns. The study of Powers and Jack (2013) indicated that while customer opportunism and switching obstacles enhance both emotional and product dissonance, consideration of flexible return policies lessens both the two dimensions. Impulse buying can indirectly influence customers' willingness to return products by directly and positively influencing product disorders (Chen, Chen and Lin, 2020).

As the retail industry has evolved, some unethical and even illegal returns have become rampant. While companies have made efforts to safeguard consumers from third-party fraud or identity theft, the harm first-party fraud committed by customers themselves causes to enterprises cannot be disregarded(Vivian Amasiatu and Hussain Shah, 2014). Identifying and dealing with such fraudulent, or opportunistic, returns can be a very tricky issue for online retailers. Deshopping is a frequent and vital category of opportunistic returns, referring to the premeditated or intentional returns of products by buyers for reasons other than the actual failure of the product (Schmidt *et al.*, 1999). Piron and Young (2000) described "retail borrowing" as the act of returning a product for a refund after using it for a particular reason and found to be free of defects. Some deshopppers are comfortable doing deshopping even though they know it is unethical, because they see no negative consequences for themselves in doing it (King and Dennis, 2006).

2.3.2 The Consequence of Product Returns

In order to increase sales, online retailers need to focus not only on pre-purchase recommendations and forecasts, but also on post-purchase returns. While returns are convenient for customers, safeguarding their rights and encouraging consumption to a certain extent, a high volume of returns can be problematic for merchants. It was reported that the three major methods used by businesses for disposing of products were returning them directly to stock, repackaging and returning to stock, and selling them as scrap (Stock and Mulki, 2009). In reverse logistics, the process of collection, inspecting and sorting, pre-processing and location and distribution consumes significant transport, inventory, warehousing, maintenance and labour costs (Min, Ko and Ko, 2006; Srivastava and Srivastava, 2006; Appriss, 2022), and some products which can not be resold are disposed of at reduced prices on the secondary market, all of which leads to a reduction in retailers' profitability.

Moreover, product returns create a lot of pressure on the environment. In both forward and reverse logistics, products need to be packaged to ensure safe delivery, and the packaging materials include paper waybills, cardboard, plastic bags, woven bags, tape, and cushioning materials such as bubble wrap and foam (Li, Feng and Liu, 2021), most of which are disposable plastic materials that are difficult to recycle. In addition, the transportation of products and the incineration of some returned products that cannot be recycled are constantly emitting greenhouse gases and some other harmful gases (Chueamuangphan et al. , 2020; Schiffer, 2019). It is estimated that returns in the United States alone generate 5 billion pounds of trash and 15 million tons of carbon emissions annually, which is equivalent to the amount of trash produced by 5 million people in a year (Schiffer, 2019).

2.3.3 Predict Product Returns

Researchers have worked diligently to develop algorithms and build models to explore how to better predict product returns. Using a machine learning approach, after building a baseline main effects model with sales, time, product type and retailer effects, Cui, Rajagopalan and Ward (2020) added higher-order interaction effects and performed model selection, ultimately using the Least Absolute Shrinkage and Selection Operator (LASSO) to obtain a sparse but robust forecasting model framework that achieves smaller forecasting errors to predict product return volume. However, a limitation of this modelling framework is that it cannot distinguish between returns due to defects and other returns. The model developed by Fu *et al.* (2016) remedies this to some extent, since it started from the inconsistency of two dimensions, the purchase phase and the shipping phase, developed the fused return propensity latent model (FRPLM) based on the generalized return propensity latent model (RPLM), which uses user profiles and product characteristics to assess the propensity of a specific user to return a specific product, and is useful in improving customer relations and identifying consumers who abuse return policies. Although both of these models use real data, it is doubtful whether the models will remain optimal when faced with large data sets. A random-walk-based local algorithm is designed to handle large-scale datasets in which each customer's product purchase and return history is represented by a weighted hybrid graph, showing good performance in predicting each customer's propensity to return products (Zhu *et al.*, 2018).

2.4 Hypotheses Development

2.4.1 Return Policy

Wang and Qu (2017) divided the return policy into three dimensions: return costs, return time limits and return effort. When return policies are used as a competitive strategy in the marketplace, although it is important for new entrant retailers to investigate customer preference for a low price no-refund policy versus a high price full-refund policy before developing a return policy (Chen and Grewal, 2013), customers do experience good emotions in reaction to the money-back guarantee, which enhances their desire to purchase and readiness to pay a higher price (Suwelack, Hogreve and Hoyer, 2011). Under some circumstances, reducing return deadlines can have the unexpected result of raising return rates (Janakiraman and Ordóñez, 2012). Davis, Hagerty and Gerstner (1998) analysed the potential reasons for differences in the level of hassle between retailers' return policies, suggesting that retailers may be more likely to offer easy return processes and lenient return policies to facilitate easy returns when product revenues cannot be consumed in the short term, product lines can be cross-sold, the value of returned merchandise for reuse is high.

Some retailers will aim to maintain competitiveness in a competitive market with generous return policies (Chen and Chen, 2017), because a generous return policy does reduce consumer perception of risk, it can go some way to increasing user loyalty and satisfaction, and stimulate purchases (Oghazi *et al.*, 2018). Moreover, if the return policy is sufficiently satisfactory, the customer’s willingness to repurchase will also be enhanced by reducing the customer's perceived risk of current and future purchases (Petersen and Kumar, 2015). Gelbrich, Gäthke and Hübner (2017) suggested that retailers could implement retention incentives to improve traditional leniency policies, which will both decrease customers' willingness to return items and increase their likelihood of repurchase. The research of Wang *et al.* (2019) supported that customers' psychological perceptions of the generosity of the return policy, the fairness of the return experience and the quality of the return experience have a positive impact on the willingness to consume.

However, the lenient return policy has increased customer willingness to buy while also increasing customers’ intention to return and adding to the burden on retailers (Janakiraman, Syrdal and Freling, 2016). And there is a risk that a lenient returns policy could be abused and ultimately lead to the company's profits being damaged. The following hypothesis is therefore proposed:

H1：The lenient return policy during the epidemic had a positive impact on the increase in returns of fashion products.

2.4.2 Additional Purchase Intention

Jeng's (2017) study indicates that the generosity of return policies has a positive relationship with purchase intentions. In e-commerce, the availability of free shipping and covering return costs for sellers is always a major concern for buyers (Lantz and Hjort, 2013). Study have shown that order frequency and order size are significantly impacted by shipping costs, and the shipping schedule that offers incentives for larger orders drives consumers to switch from to large orders (Lewis, 2006). Part of the increase in order size is actually due to the increased additional willingness to purchase. Additional willingness to buy outside of the original purchase plan, often originating from discounts and offers, or other activities that make customers feel less pressured to buy and return.

According to the findings, a permissive delivery policy and free shipping fee are linked to higher order frequency, a decline in the average purchase value, a rise in the likelihood of returns, and an increase in the average value of returned goods (Lantz and Hjort, 2013). Some online retailers will require users to pay a certain amount before offering free delivery, otherwise they will need to charge shipping fees. Such a threshold-based free shipping policy may boost consumption to a certain extent, but for some customers, when the total amount of products they intend to purchase does not reach the condition of free delivery, they will be more possible to buy products that they have already decided to return in the future at the time of payment. In addition, threshold-based free shipping policy can decline purchase incidence (Lepthien, 2019).

In this case, the restrictive free delivery policy instead indirectly leads to an increase in the return rate, and possibly contributed to the occurrence of some opportunistic behaviour (Wachter *et al.*, 2012). Thus, the following hypothesis is proposed:

H2：The additional purchase intention during the epidemic had a positive impact on the increase in returns of fashion products.

2.4.3 Perceived Risk

The definition of perceived risk was originally proposed by Bauer (1967) :“Consumer behavior involves risk in the sense that any action of a consumer will produce consequences which he cannot anticipate with anything approximating certainty, and some of which at least are likely to be unpleasant”. Hassan *et al.* (2006) has developed a reliable scale to measure perceived risk in e-commerce, with dimensions consisting of “Perceived Financial Risk, Perceived Performance Risk, Perceived Time-loss Risk, Perceived Social Risk, Perceived Physical Risk, Perceived Psychological Risk, Perceived Source Risk, Perceived Privacy Risk”, providing direction for subsequent research on perceived risk. The research of Pires, Stanton and Eckford (2004) showed that the frequency of online purchases did not affect perceived risk, but for low engagement products, satisfaction with previous online purchases was negatively related to perceived risk of future purchases. Also for Chinese online shoppers, past experience with this product or brand, in addition to product information, payment security and money back guarantees, and the brand of purchase, are effective strategies for reducing the the non-personally perceived risk of clothing purchases (Zheng, Favier and Huang, 2012). Zheng, Favier and Huang (2012) also suggested that product performance risk was the number one major risk ranked for consumers in the apparel industry. In using risk-treatment activities to reduce consumers' perceived risk, the perceived benefits of the type of activity and the consumer's level of caution about monetary loss (Dowling and Staelin, 1994). In the realm of online shopping, it is most common to reduce customers' perceived risk of purchasing a product and increase their willingness to buy through a generous return policy, such as a money-back guarantee(Chen and Chen, 2017). Thus, the following hypothesis is proposed:

H3：The perceived risk during the epidemic had a positive impact on the increase in returns of fashion products.

2.5 Research Gap

There has been much previous literature examining the factors or conditions that affect product returns, and following the boom in e-commerce, there has been a growing body of literature examining returns of online fashion products. However, with the explosion of the COVID-19 pandemic, fashion retailers have been sluggish and returns are increasing at a time when sales are already limited. This study fills this gap by looking at changes in individual consumer returns and exploring the factors that influenced the growth of consumer returns during the pandemic.

Chapter 3 Methodology

3.1 Chapter Overview

This chapter introduces the research philosophy, research approach, research methodology and research strategy of this study in broad accordance with the research onion framework (see Figure 1). As this study used secondary questionnaire data, sampling and designing and collecting questionnaires are missing. After a brief presentation of the data, the focus is on the analysis of the data which will be important in the rest of the study. Finally, ethical considerations are described.

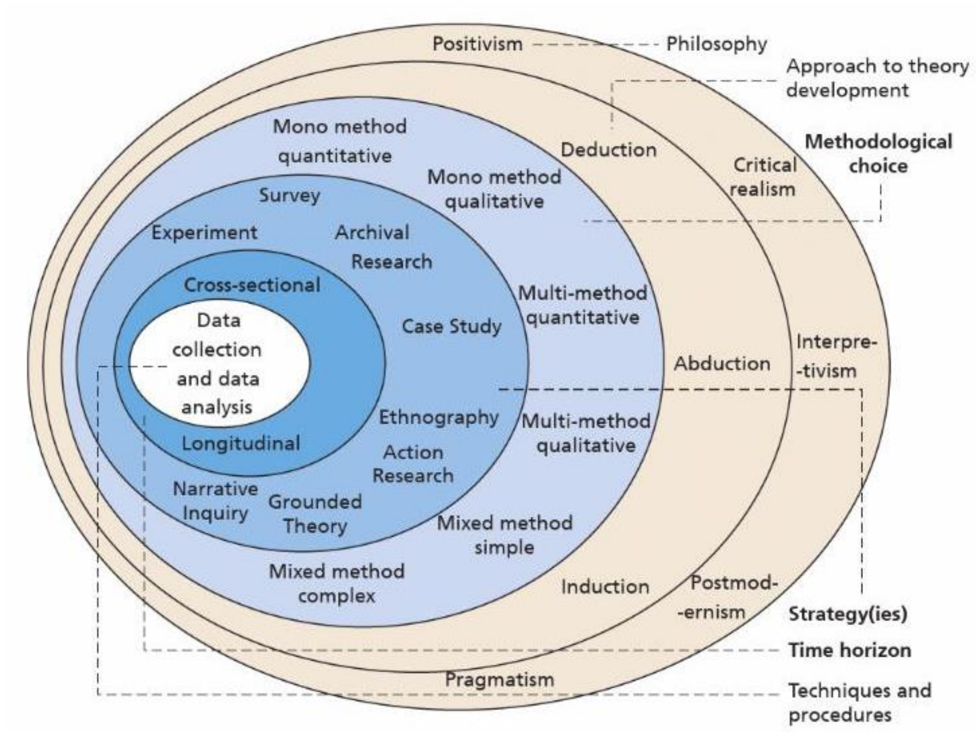

Figure 1 The research onion framework

Source: Saunders et al.(2009)

3.2 Research Philosophy

According to the latest edition of Saunders'(2019) book, research philosophy can be classified into five types: positivism, critical realism, interpretivism, postmodernism and pragmatism. The positivist philosophy applied in this study, since it firmly upholds a scientific empiricist approach, using pure data and scientific experimental techniques to describe, explain and evaluate facts without the influence of human interpretation or bias (Saunders et al., 2019).

In order to avoid influencing the outcomes of the final analysis and discussion, the researchers are advised to try to act only as an external participant in the data collection process during the internet survey (Saunders et al., 2019). This means remaining impartial and refraining from interfering with the respondents' judgement. In addition, positivism guides the researcher to not necessarily need to formulate hypotheses based on existing theories (Saunders et al., 2019), as hypotheses are used to guide experiments and the results of the experiments can be used to test the hypotheses to see if they are consistent with observable and quantifiable facts. The data used in this study is secondary questionnaire data, but the questionnaires were collected through experienced researchers. And the hypotheses in this study are based on existing views and the results will ultimately be obtained by means of hypothesis testing.

3.3 Research Approach

Additionally, there are three research approaches in social science, which are deductive, inductive, and abductive, according to Saunders et al. (2019). The deductive approach calls for the researcher to construct a theory from reading academic literature, formulate a testable statement or hypothesis, and then test the proposition or hypothesis by analysing the data to determine the analysis's findings (Saunders et al., 2019). The theory is supported if the analysis's findings are consistent with its premises or hypothesis. Induction and abductive, unlike deduction, both require gathering information and researching phenomena before formulating or altering theories, except that abductive need to go through the process of hypothesis testing again after this. (Saunders et al., 2019).

Although some followers of the inductive method may also find the deductive process somewhat rigid, this does not prevent the deductive method from predominating in the natural sciences (Saunders et al., 2019). The deductive approach is used in this study because it is typically associated with positivism and because this paper presents a series of hypotheses based on the literature about what factors affecting customer returns of fashion products during the epidemic, and the hypotheses need to be tested by statistical methods. The deductive approach is therefore the most appropriate approach for this study.

3.4 Research Method

Quantitative is used in this study instead of the other two research methods, qualitative and mixed. It is crucial to distinguish between quantitative and qualitative research because the former typically uses data that can be converted into numerical form, such as survey data, to measure and analyse relationships between variables, whereas the latter frequently uses non-numerical data, such as text and audio recordings (Saunders et al., 2019).

Having identified positivism as the research philosophy and the deductive as the research approach, the quantitative research design is usually strongly related to both in business and management research, and therefore it can be almost certain to be used. Furthermore, as this study uses survey data, the aim is to ascertain what factors affecting customer returns of fashion products during the epidemic, essentially analysing the relationship between variables, and statistical methods such as the chi-square test will be used next, in line with the definition of quantitative research. Thus, quantitative research design is more applicable to this study than other methods, allowing the researcher to be objective, and the findings using it are more generalisable and replicable than those using qualitative because the former often use probability sampling to draw subjects for the study whereas the latter do not (Saunders et al., 2019).

3.5 Research Strategy

Different research designs correspond to different research strategies, which describe the way in which the researcher will collect information or data. Ethnography, action research, grounded theory and narrative inquiry are four strategies that available for qualitative research, while for quantitative research it may involve research strategies that include experiments, survey, archival and documentary research, and case study (Saunders et al., 2019). Considering the practicability and practicality of the practice, the survey strategy is applied to this study. The use of questionnaires in surveys is a common method in business and management research since it makes it affordable to collect data from a lot of respondents, allows for comparison, and easy to interpret and comprehend.

In this study, the survey strategy permits the collection of preferences and information from respondents who had experienced returns of online apparel-type products during the epidemic and the subsequent quantitative analysis of the data using descriptive analysis and other statistical methods to measure the relationships between factors affecting returns and generate statistically significant results.

3.6 Introduction to the Questionnaire

The questionnaire used in the study was collected online through the Qualtrics platform, with a total sample of 528 questionnaires being collected. As some of the questions in the questionnaire are not relevant to this study, only those questions that will be used to analyse for this study are presented.

In addition to the demographic questions, a total of 8 scale questions, 4 multiple choice questions and 3 single choice questions appear in this paper, the purpose and general content of the questions is shown in the Table 1 below.

Type	Purpose	General content
Scale questions	As independent variables after using exploratory factor analysis to reduce dimensions	Preference for shopping with retailers where returns can be taken back to store.
		Preference for ordering more items if retailers offer free returns.
		Preference for purchasing additional items that will be returned if only threshold-based free shipping was provided.
		Preference for returning fewer fashion purchases if I had to pay for it.
		Preference for checking the length of time allowed for returns before shopping.
		Preference for changing mind and return items when retailers offer a longer return period.
		Preference for returning items if it involves more effort.
		Preference for returning items if there are more return options.
Multiple choice questions	Descriptive analysis and Crosstabulation	The frequent reasons for returning fashion items bought online.
		The fashion-purchasing circumstances that will be regretted and items will be more likely to be returned.
		The circumstances would make it less likely to return fashion items bought online.
		The circumstances would make it less likely to return fashion purchases in-store.
Simple choice questions	As dependent variable	Quantify fashion returns during the COVID-19 pandemic compared to before.
	Descriptive analysis	Choose preferred way to return fashion purchases.
	Descriptive analysis and Crosstabulation	Choose length of time to take before returned unwanted fashion products.

Table 1 Presentation of the questions will be used

3.7 Data Analysis

The software used in the study was Excel and IBM SPSS Statistics 25. Excel was used for some of the data pre-processing work and IBM SPSS Statistics 25 was used for the remainder of the data pre-processing and for the subsequent statistical analysis.

3.7.1 Data Pre-processing

Data pre-processing should be done at the onset because not all of the questionnaire data obtained is pertinent and may be used for analysis. Data pre-processing makes it possible for the data to be clean and makes it easier to analyse the data later. The primary goals of the data pre-processing carried out for this study were to eliminate outliers and some samples that had missing values. Due to some technical glitches or problems with respondents' wishes and attitudes, the questionnaire collected online will have some invalid data that need to be removed. In this study, as the target respondents of the questionnaire collection were those who had experience in purchasing fashion products during the COVID-19 pandemic, data from those samples who had no experience in fashion shopping during the epidemic, were unwislling to participate in the survey and were flagged as fraudulent types would be deleted; to ensure the reliability and validity of the questionnaire data, samples who did not fill in the questionnaire completely, completed the questionnaire but some of the answers were not collected due to technical problems, did not complete the quality test questions in the questionnaire correctly were also considered as invalid data and were deleted.

3.7.2 Chi-Square Test

The chi-square test is a non-parametric statistic and allows to analyse categorical data frequency data, can de divided into the chi-square goodness-of-fit test and, which requires a frequency of greater than 5 for each cell in a 2*2 cross-tabulation. (Hinton, McMurray and Brownlow, 2014a). There are six assumptions for using the chi-square test, which are that the data can only be frequencies and counts, that categorical variables are coexistently exclusive, that groups must be independent when comparing two groups of tests, that each subject can only give data to one cell, that the two variables in the test are categorical variables and that the value of the cell is expected to be 5 (McHugh, 2013). The chi-square goodness-of-fit test compares whether the answer to a question is significantly consistent with the expected pattern, or frequency, of the response. In this study, the chi-square goodness-of-fit test is used to test for significant differences in the frequencies of the options in the multiple choice questions; chi-square test of independence is used to test used to test for cross-tabulation between multiple choice and single choice questions.

3.7.3 Reliability Test

The definition of reliability is that “the extent to which a measurement of a phenomenon provides stable and consist result”, and the Cronbach Alpha coefficient is the most popular internal consistency measure (Taherdoost, 2016), whose calculation ” is based on the number of items (i.e. the number of questions on a questionnaire) and the average inter-item correlation” (Hinton, McMurray and Brownlow, 2014b). There is generally no such thing as a perfectly reliable test with an internal consistency of 1, but a value of Cronbach Alpha greater than 0.75 would be considered a relatively good value to represent a reliable questionnaire (Hinton, McMurray and Brownlow, 2014b).

3.7.4 Exploratory Factor Analysis

This study utilised exploratory factor analysis construct convergent validity, which was defined as " the extent that different measures of the same construct converge or strongly correlate with one another" (Taherdoost, 2016). Exploratory factor analysis is a common method of dimensionality reduction, seeks to discover that a small number of factors explain most of the original variables to save time and make the interpretation easier, and that the factors are often difficult to measure directly as latent variables. It can be used for both continuous and categorical variables. This study uses principal component analysis to extract factors as a first step in dimensionality reduction, and then rotates the factors by the orthogonal technique Varimax rotation to minimise the number of variables that have high loadings on each factor (Yong and Pearce, 2013). Next the number of factors extracted was determined by eigenvalue and gravel plot tests. The rule that was mostly used was to retain all factors with eigenvalues greater than 1. Finally the factors were represented as raw variables using a factor score coefficient matrix and given factors (Yong and Pearce, 2013). These are the approximate steps of exploratory factor analysis. However, the limitations of exploratory factor analysis are that renaming the extracted factors is subjective, sometimes the names of the factors may not accurately reflect the variables they contain, and the results may be difficult to replicate (Yong and Pearce, 2013).

3.7.5 Logistic Regression

The models commonly used when encountering studies of this type exploring influencing factors are linear regressions. Linear regression is used to identify the relationship between a continuous dependent variable and one or more independent variables using the least squares method, which is relatively simple, fast and results in a mathematical formula that is easy to interpret, making it widely used and used in various fields (IBM, no date a). However, this study uses a logistic regression model. The major difference between linear regression and logistic regression is that the former's dependent variable must be continuous, whereas the latter's is a categorical variable and is often used in binary classification problems. Based on a given dataset of independent variables, logistic regression calculates the likelihood that an event will occur, such as win or lose. Given that the result is a probability, the dependent variable's range is 0 to 1 (IBM, no date b). The logical function is expressed as follows, where y is the dependent variable and x_i is the independent variable.

$$logistic\ function = \frac{1}{1 + e^{-y}}$$

$$ln\left(\frac{y}{1-y}\right) = \beta_0 + \beta_1 x_1 + \cdots + \beta_i x_i$$

The β_i parameter in the equation is obtained by maximum likelihood estimation (IBM, no date b). In order to find the best fit for the log odds, this approach iteratively evaluates various beta values. The log likelihood function is created after each of these iterations, and logistic regression aims to maximise this function to get the most accurate parameter estimate (IBM, no date b). Once the logistic regression model has been obtained, so as to check whether the assumptions of the model are correct, the Hosmer-Lemeshow goodness-of-fit test, a common method, will be used to assess the fit of the model (Bartlett, 2014).

As the secondary data used in this study did not contain the continuous numerical variables that would be required as dependent variables in a multiple linear regression, the solution to continue exploring the factors influencing fashion retailing during the pandemic was to choose a logistic regression model that only required the dependent variable to be a categorical variable. The samples selected from the questionnaire "How would you quantify your fashion returns during the COVID-19 pandemic compared to before?" with the answer "more returns" were extracted and marked as 1, while those who selected other answers were marked as 0, and the newly marked 1s and 0s were set to a new binary variable called "returnmore". When "returnmore" takes a value of 1, it means that the respondent returned more goods during the pandemic than before, and vice versa, meaning that no more goods were returned.

3.8 Ethical Consideration

Although this study uses secondary survey data, ethical issues have been well considered during the research. Ethics approval for this research was granted, with ERGO approval number 76426. The original survey data is designed and collected by experienced researchers and has been ethically approved. This study conducts the analysis as part of the team of researchers who were declared to have access to the survey data. The terms and conditions of using the data are that the survey data cannot be edited directly on the Qualtrics platform.

The content of the questionnaire does not contain sensitive personal information about the respondents. There are only five questions in the questionnaire that directly relate to the data subject: age, gender, education, current employment status and current individual annual income, all of which are single choice questions, and no disclosive ID codes have been used. In addition, for current individual annual income, respondents could choose not to fill in the question, and for age, the options were set as intervals rather than specific numbers. It is therefore difficult to identify individuals based on these characteristics.

Chapter 4 Analysis and Results

4.1 Chapter Review

The analysis and results began with a descriptive analysis showing the demographic information of the respondents and the frequency distribution of some questions in the questionnaire, followed by an exploratory factor analysis after passing the reliability test, and finally the three factors obtained by dimensionality reduction were brought into the logistic regression equation, yielding significant results.

4.2 Descriptive Analysis

4.2.1 Demographic Information of Respondents

The demographic information of the respondents included in the collected questionnaire data are gender, age group, education level, employment status and individual annual income, etc. According to the Table 2 below, it illustrates that the number of male and female respondents is m basically the same; since the questionnaire is targeted at adults aged 18 years and above, the respondents over 18 were divided into six groups, with a roughly even distribution, the largest group being 25-34 years old (21.15%), followed by 18-24 and 35-44 years old, both at 20%, and the smallest group over 65 years old (11.11%); the education level of the respondents was concentrated in the undergraduate degree (36.11%), followed by A-level or equivalent (24.15%). The “Employed full-time” was the largest group participating in the survey, accounting for 45.09% of the total, while “Housewife/Househusband” was the smallest one , accounting for 2.35%; 65.71% of respondents had an individual annual income of less than £29,999, with roughly equal numbers in the Under £10,000, £10,000 - £19,999 and £20,000 - £29,999 ranges, all accounting for approximately 20% of the total.

Variable	Option	Frequency	Percent (%)	Cumulative percent (%)
Gender	Female	232	49.573	49.573
	Male	231	49.359	98.932
	Non-binary / third gender	4	0.855	99.786
	Prefer not to say	1	0.214	100.000
Age group	18-24 years old	95	20.299	20.300

Variable	Option	Frequency	Percent (%)	Cumulative percent (%)
	25-34 years old	99	21.154	41.453
	35-44 years old	94	20.085	61.538
	45-54 years old	73	15.598	77.137
	55-65 years old	55	11.752	88.889
	Over 65 years old	52	11.111	100.000
Education level	Vocational / technical qualification	60	12.821	12.821
	Bachelors degree	169	36.111	48.932
	Less than A-level or equivalent	49	10.470	59.402
	A-level or equivalent	113	24.145	83.547
	Masters degree	67	14.316	97.863
	Doctorate degree	7	1.496	99.359
	Other	3	0.641	100.000
Employment status	Employed full-time	211	45.085	45.085
	Employed part-time	83	17.735	62.821
	Retired	59	12.607	75.427
	Student	59	12.607	88.034
	Other	16	3.419	91.453
	Unemployed, looking for work	15	3.205	94.658
	Unemployed, not looking for work	14	2.991	97.650
	Housewife / Househusband	11	2.350	100.000

Variable	Option	Frequency	Percent (%)	Cumulative percent (%)
Individual annual income	Under £10,000	101	21.581	21.581
	£10,000 - £19,999	99	21.154	42.735
	£20,000 - £29,999	105	22.436	65.171
	£30,000 - £39,999	55	11.752	76.923
	£40,000 - £49,999	41	8.761	85.684
	£50,000 - £74,999	30	6.410	92.094
	Over £75,000	7	1.496	93.590
	Prefer not to say	30	6.410	100.000
Total		468		

Table 2 Demographic information of respondents

4.2.2 Frequency Distribution

4.2.2.1 Changes In the Quantity of Returned Goods

From the Table 3 and the Figure 2, it can be obtained that 41% of the respondents do not believe that there is a difference in the number of returns they made before and after the pandemic regarding fashion products, 25% believe that they returned more during the pandemic than before, and 14% believe that they returned more before the pandemic than during the pandemic. Surprisingly, 16% had never returned anything during the pandemic.

How would you quantify your fashion returns during the COVID-19 pandemic compared to before?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Fewer returns	63	13.5	13.5	13.5
	Same number	193	41.2	41.2	54.7
	More returns	118	25.2	25.2	79.9
	Not sure	18	3.8	3.8	83.8

	I have not returned anything during the pandemic	76	16.2	16.2	100.0
	Total	468	100.0	100.0	

Table 3 Changes in the quantity of returned goods

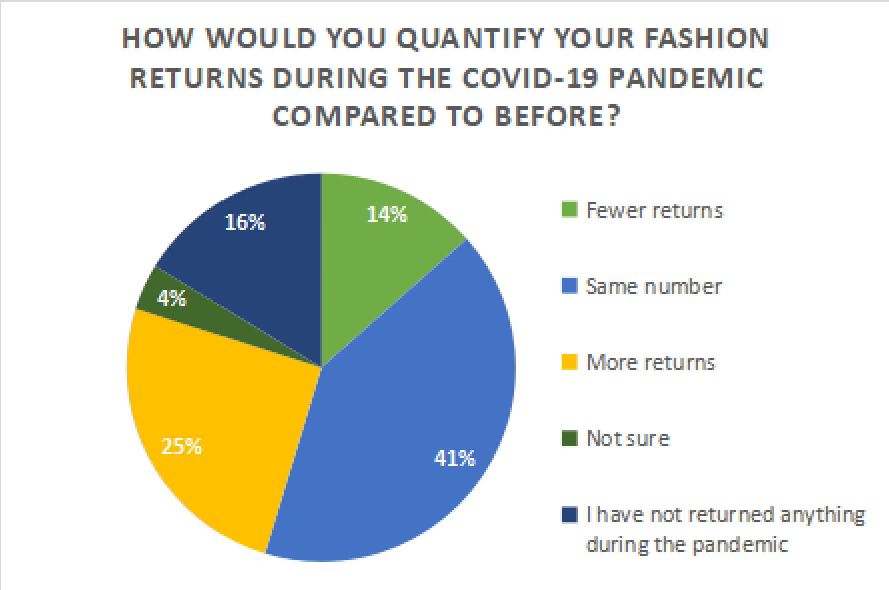

Figure 2 Changes in the quantity of returned goods

4.2.2.2 Length of Time to Consider Returns

The Table 4 and Figure 3 show that 43% of the respondents consumed only about 2-3 days to consider whether to return the product, and 39% took a week to decide whether to return it, and that was all within a reasonable return period. 8% took longer, around 2 weeks, to decide whether to return the product, which is a bit slow in comparison and already beyond the return period set by some merchants.

On average, how long did it take before you returned unwanted fashion products?					
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Around 2-3 days	200	42.7	42.7	42.7
	Around a week	183	39.1	39.1	81.8
	Around two weeks (i.e., 14 days)	37	7.9	7.9	89.7

	As long as possible until the final return date	9	1.9	1.9	91.7
	I have never returned a product	38	8.1	8.1	99.8
	I often go beyond the final return date and hope for goodwill from the retailer	1	.2	.2	100.0
	Total	468	100.0	100.0	

Table 4 Length of time to consider returns

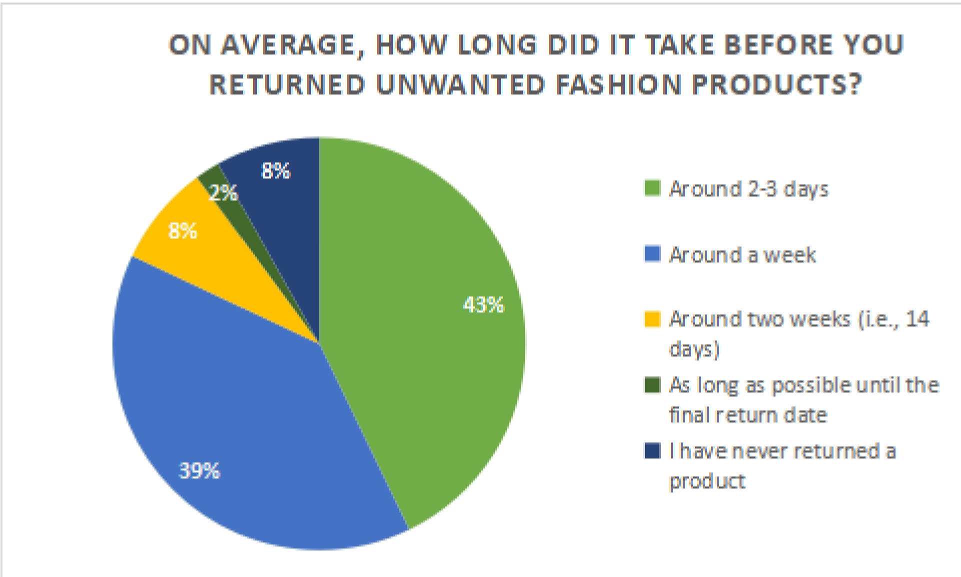

Figure 3 Length of time to consider returns

4.2.2.3 Preferred Way to Return

According to Table 5 and Figure 4, the respondents' preferred return methods are concentrated in three main types, in-store (28%), Parcel shop drop-off (26%) and Royal mail (24%) in that order, with little difference in the popularity of the three methods. There are also a significant number of people who prefer to return goods via courier pick-up (16%) and fewer people return goods via locker (5%).

What is your preferred way to return fashion purchases?				
	Frequency	Percent	Valid Percent	Cumulative Percent

Valid	In-store	132	28.2	28.2	28.2
	Royal mail	115	24.6	24.6	52.8
	Parcel shop drop-off	121	25.9	25.9	78.6
	Courier pick-up	73	15.6	15.6	94.2
	Other (please specify)	3	.6	.6	94.9
	Locker	24	5.1	5.1	100.0
	Total	468	100.0	100.0	

Table 5 Preferred way to return

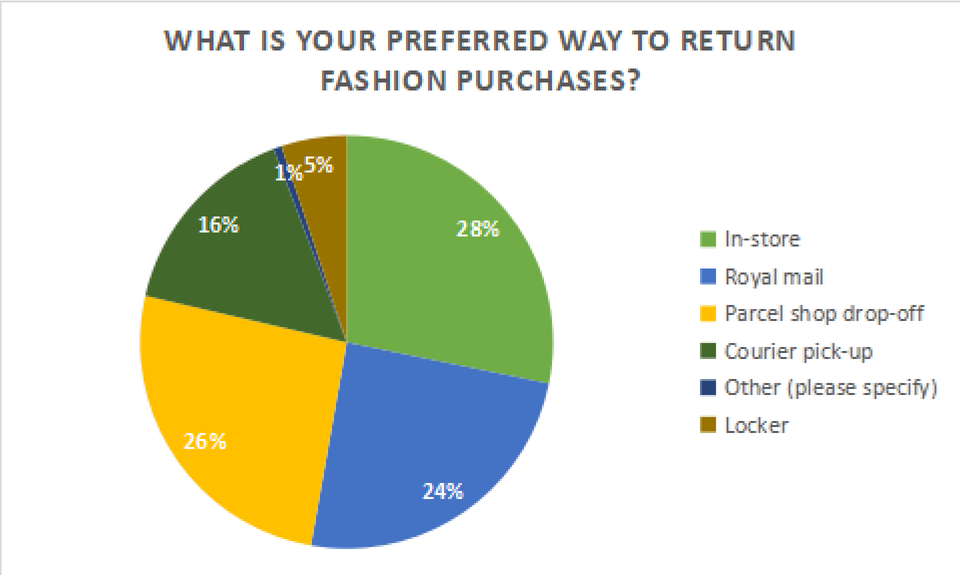

Figure 4 Preferred way to return

4.2.2.4 The Time for Regretting Purchases

According to the Table 6, The p-value of 0 rejects the original hypothesis, indicating that the proportion of options chosen is significantly different . The moment when people are most likely to regret buying a fashion product is when they find the same product cheaper on another website (195), with a response rate of 21.5%, the only selection chosen by more than a third of people (41.7%). Apart from that, about 20% of the respondents thought "When be down / sad / lonely / frustrated" (22.4%), "Items on sale" (22.6%), "Feel bored during lockdown", "Read some negative reviews", "Late at night", "Late at night", "Late at night" and "Late at night". "Feel bored during lockdown" (22.2%), "Read some negative reviews" (18.6%), " Late at night" (17.3%) would be prone to regret. "At weekends" (2.8%), "Faster delivery elsewhere" (3.8%), "Made them via guest checkout" (3.6%) were the three least selected options. In general, people are most likely to regret when they feel low and when they are mentally unbalanced if they think their order is not worth it.

$regrettime Frequencies						
		Responses		Percent of Cases	X^2	P
		N	Percent			
$regrettime[a]	Right after payday	49	5.4%	10.5%	375.828	0.000***
	Late at night	81	8.9%	17.3%		
	At weekends	13	1.4%	2.8%		
	When be down / sad / lonely / frustrated	105	11.6%	22.4%		
	Feel bored during lockdown	104	11.5%	22.2%		
	Misread the product information	131	14.5%	28%		
	Items on sale	106	11.7%	22.6%		
	Cheaper elsewhere	195	21.5%	41.7%		
	Read some negative reviews	87	9.6%	18.6%		
	Faster delivery elsewhere	18	2.0%	3.8%		
	Made them via guest checkout	17	1.9%	3.6%		
Total		906	100.0%	193.6%		
a. Dichotomy group tabulated at value 1.						

Table 6 The time for regretting purchases

4.2.2.5 Return Reason

From Table 7, the p-value of 0 rejects the original hypothesis, indicating that the proportion of options chosen is significantly different. The inappropriate size of the garment was the most common reason for return (331), with a response rate of 26.8% and 86% of respondents choosing this option. This was followed by the options "I did not like the style / colour" (214), "Not as expected" (195), "Ordered a selection (176)", each receiving approximately 50% agreement. People were relatively the least likely to have a choice because of 'Cheaper elsewhere', 'Better product elsewhere', 'Ordered it for a specific use / occasion and no longer need it", with only around 5% of customers returning products for these reasons. In general, the reasons for returns were mainly due to uncertainty about the product, including size, quality, colour, style, etc. Interestingly, in conjunction with the Table 6 above, it shows that while customers may regret their order due to 'cheaper elsewhere', very few actually return it for this reason. The option "I ordered it for a specific use/occasion and no longer need it" is to some extent in a fraudulent return.

$returnreason Frequencies						
		Responses		Percent of Cases	X²	P
		N	Percent			
$returnreason a	Ordered a selection	176	14.2%	45.7%	935.981	0.000***
	Change mind	85	6.9%	22.1%		
	I regretted my purchase	56	4.5%	14.5%		
	I did not like the style / colour	214	17.3%	55.6%		
	I ordered it for a specific use / occasion and no longer need it	21	1.7%	5.5%		
	Defect / faulty	77	6.2%	20.0%		
	Did not fit	331	26.8%	86.0%		
	Not as ordered	37	3.0%	9.6%		
	Not as expected	195	15.8%	50.6%		
	Cheaper elsewhere	22	1.8%	5.7%		
	Better product elsewhere	23	1.9%	6.0%		
Total		1237	100.0%	321.3%		
a. Dichotomy group tabulated at value 1.						

Table 7 Frequent reasons for returns

4.3 Crosstabulation

4.3.1 Less return in-store and preferred way to return

A cross-tabulation of the circumstances what will make respondents less likely to return fashion purchases in-store and their preferred way to return fashion products is shown as below.The number of multiple choice and single choice questions with the option "other" was too low and was therefore removed. As can be seen from the table, the significant p-value is 0.019, which is less than 0.05, rejecting the original hypothesis that there is no difference between the two questions, indicating that there is a significant difference between the multiple choice question and the single choice question.

From the Table 8 and stacked bar charts Figure 5, the options that the shop is too far away, too difficult to get to and inconvenient opening times were the most frequently selected situations that made people reluctant to return fashion products in-store, with a total of 402 out of 463 people, and at least 80% of people choosing this option for any return, followed by 'there is likely to be a long queue" (255), "it is easier / saves time to return via courier / post / etc" (235) and "I need to go to customer services rather than any tills", while the least number of people (29), used the excuse of having to wear a mask when going to the shops.

For those who prefer to return to the store, "the store is far away / difficult to reach / has inconvenient opening times" remains the biggest factor influencing their willingness to do so, and The ranking of the remaining factors is also consistent with the overall question. However, it can be noted that significantly fewer people (24.2%) choose "it is easier / saves time to return via courier / post / etc." than those who prefer other methods of return (all around 60%); and the frequency of "there is likely to be a long queue" and "I need to go to customer services rather than any tills" is lower than the other groups who prefer other return methods, which also applies to the group that prefers royal mail. The group of other return methods did not differ significantly in their choice of reasons that made the willingness to return goods in-store low.

$lessreturninstore*waytoreturn Crosstabulation

			What is your preferred way to return fashion purchases? - Selected Choice					Total		
			In-store	Royal mail	Parcel shop drop-off	Courier pick-up	Locker		X²	P
$lessreturninstore[a]	I need to wear a mask	Count	7	6	7	7	2	29	29.79	0.019
		% within $lessreturninstore	24.1%	20.7%	24.1%	24.1%	6.9%			
		% within waytoreturn	5.3%	5.2%	5.8%	9.7%	8.3%			
	there is likely to be a long queue	Count	66	58	69	47	15	255		
		% within $lessreturninstore	25.9%	22.7%	27.1%	18.4%	5.9%			
		% within waytoreturn	50.0%	50.4%	57.5%	65.3%	62.5%			
	I need to go to customer services rather than any tills	Count	10	10	23	15	4	62		
		% within $lessreturninstore	16.1%	16.1%	37.1%	24.2%	6.5%			
		% within waytoreturn	7.6%	8.7%	19.2%	20.8%	16.7%			
		Count	115	103	100	65	19	402		

	the store is far away / difficult to reach/ has inconvenient opening times	% within $lessreturninstore	28.6%	25.6%	24.9%	16.2%	4.7%			
		% within waytoreturn	87.1%	89.6%	83.3%	90.3%	79.2%			
	it is easier / saves time to return via courier / post / etc.	Count	32	72	73	44	14	235		
		% within $lessreturninstore	13.6%	30.6%	31.1%	18.7%	6.0%			
		% within waytoreturn	24.2%	62.6%	60.8%	61.1%	58.3%			
Total		Count	132	115	120	72	24	463		
	Percentages and totals are based on respondents.									
	a. Dichotomy group tabulated at value 1.									

Table 8 Crosstabulation of less return in-store and preferred way to return

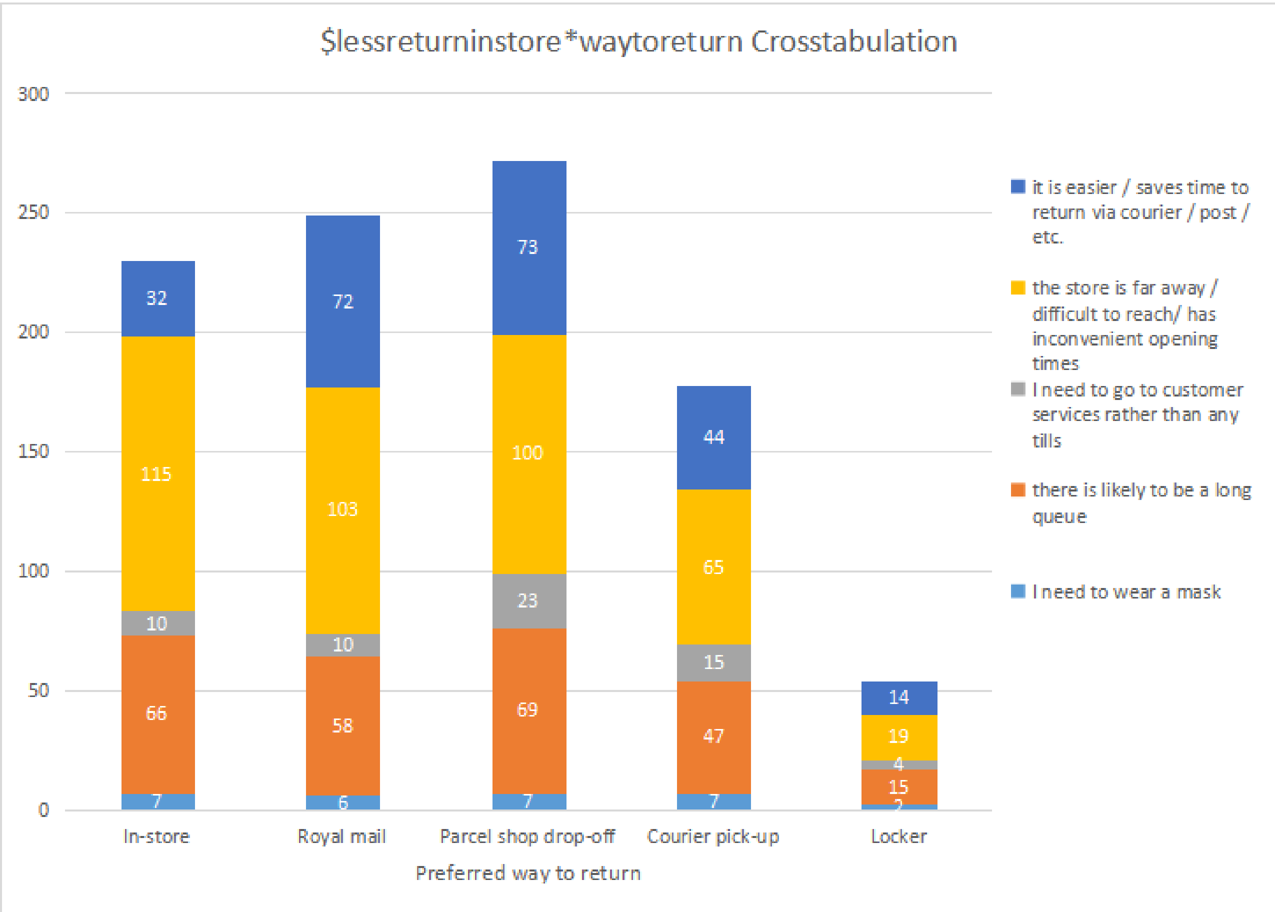

Figure 5 Crosstabulation of less return in-store and preferred way to return

4.3.2 Pre-purchase information and gender

From Table 1, the p-value is 0.965, indicating that there is no enough reason to reject the original hypothesis, and no significant difference between gender on pre-purchase information. Therefore only the frequency of pre-purchase information will be analysed. Better sizing chart" was the next most popular choice (312), followed by "Suggesting suitable sizes based on previous purchase" (241), "Photos of real customers wearing the item" (231), "Better product description / pictures " (211), "Customer reviews" (182), "A price matching service / best price guarantee " (128). The least is "A customer hotline to ask about item details". The respondents' choices show that what matters most to customers is always the uncertainty of the product, in particular the size of the item and how the garment will look on them.

$prepurchaseinfo*gender Crosstabulation							
			gender		Total	X^2	P
			Male	Female			
$prepurchaseinfo[a]	Better product description / pictures	Count	103	108	211	3.564	0.965
		% within $prepurchaseinfo	48.8%	51.2%			
		% within gender	45.2%	49.1%			
	Photos of real customers wearing the item	Count	110	121	231		
		% within $prepurchaseinfo	47.6%	52.4%			
		% within gender	48.2%	55.0%			
	Customer reviews	Count	98	84	182		
		% within $prepurchaseinfo	53.8%	46.2%			
		% within gender	43.0%	38.2%			
	Better sizing chart	Count	161	151	312		
		% within $prepurchaseinfo	51.6%	48.4%			
		% within gender	70.6%	68.6%			
	A price matching service / best price guarantee	Count	64	64	128		
		% within $prepurchaseinfo	50.0%	50.0%			
		% within gender	28.1%	29.1%			
	A customer hotline to ask about item details	Count	12	12	24		
		% within $prepurchaseinfo	50.0%	50.0%			
		% within gender	5.3%	5.5%			
		Count	51	61	112		

	Live chat to ask about item details	% within $prepurchaseinfo	45.5%	54.5%			
		% within gender	22.4%	27.7%			
	Chat-bot	Count	24	21	45		
		% within $prepurchaseinfo	53.3%	46.7%			
		% within gender	10.5%	9.5%			
	Virtual catwalk	Count	43	46	89		
		% within $prepurchaseinfo	48.3%	51.7%			
		% within gender	18.9%	20.9%			
	Virtual fitting rooms	Count	48	46	94		
		% within $prepurchaseinfo	51.1%	48.9%			
		% within gender	21.1%	20.9%			
	Suggesting suitable sizes based on previous purchase	Count	116	125	241		
		% within $prepurchaseinfo	48.1%	51.9%			
		% within gender	50.9%	56.8%			
Total		Count	228	220	448		
Percentages and totals are based on respondents. a. Dichotomy group tabulated at value 1.							

Table 9 The crosstabulation of pre-purchase information and gender

4.4 Reliability Test

As the questionnaire used in the study did not refer to a well-established Likert scale that had been used in other previous studies, the dimensioning was not conducted for the time being. All the self-developed scale questions were tested for reliability in SPSS. The items that seriously lowered the value of Cronbach's Alpha were removed according to the Item-Total Statistics table, and the final value of Cronbach's Alpha was 0.600 (see Table 10). The Cronbach's Alpha of 0.600 is indeed not high enough and most studies have used 0.7 as a measure of questionnaire reliability. However, as this questionnaire was written internally, 0.60 can be considered an moderate reliability (Taherdoost, 2016). Therefore the questionnaire used in this study can also be considered reliable.

Reliability Statistics	
Cronbach's Alpha	N of Items

.600	10

Table 10 The result of reliability test

4.5 Exploratory Factor Analysis

Since the questionnaire did not refer to the established Likert scale and the dimensions had not yet been classified, exploratory factor analysis was first conducted. The maximum variance method was chosen for factor rotation in SPSS, and then the Table 11 was obtained. As can be seen, the KMO coefficient was 0.658, indicating that the correlation between the variables was acceptable. Furthmore, the Bartlett's Test of Sphericity was passed with a significance of 0, which is less than 0.05, indicating that these variables are suitable for factor analysis.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.680
Bartlett's Test of Sphericity	Approx. Chi-Square	376.361
	df	36
	Sig.	.000

Table 11 The first result of KMO and Bartlett's test

As can be seen from the Table 12, after performing the factor rotation, only three factors with eigenvalues greater than one were extracted, and this is also indicated by the fact that the straight line in the scree plot (see Figure 6) suddenly goes from steep to flat when the component number is three. These three factors explained 20.819%, 16.240% and 13.716% of the variance respectively, cumulatively explaining 50.775% of the variance.

Total Variance Explained									
Com-ponent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	2.185	24.275	24.275	2.185	24.275	24.275	1.874	20.819	20.819
2	1.369	15.211	39.486	1.369	15.211	39.486	1.462	16.240	37.059
3	1.016	11.290	50.775	1.016	11.290	50.775	1.234	13.716	50.775

4	.956	10.617	61.392						
5	.863	9.584	70.976						
6	.764	8.490	79.465						
7	.667	7.410	86.875						
8	.624	6.937	93.813						
9	.557	6.187	100.000						

Extraction Method: Principal Component Analysis.

Table 12 The first result of total variance explained

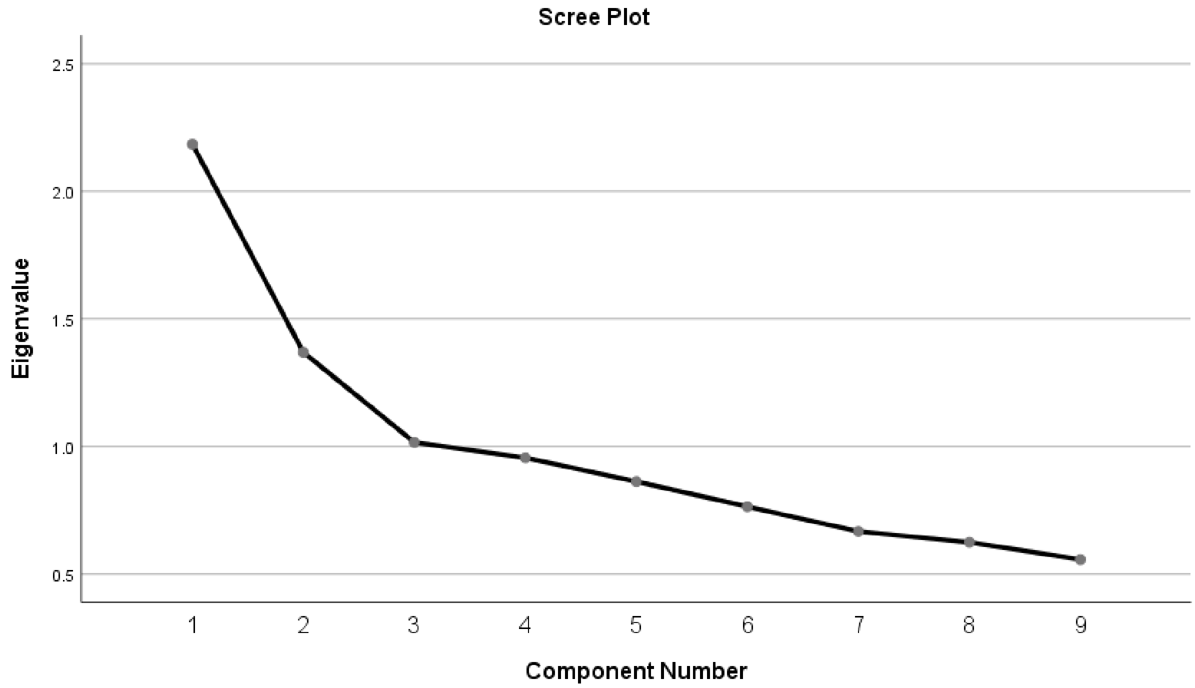

Figure 6 Scree plot

With empty cells denoting coefficients less than 0.5, the rotated component matrix's function is to assist in identifying which component each variable is assigned to. The fact that the variable " Comfortable with returns " is not separated into any components in the table is a clear indication that its contribution to any component is not apparent enough (see Table 13). Consequently, it will be removed. However, in this instance, a further exploratory factor analysis is required.

Rotated Component Matrix			
	Component		
	1	2	3
More returns with more options	.724		

More returns with less effort	.718		
More returns with longer period	.586		
Fewer returns if charged	.555		
Purchase items will be returned for free delivery		.806	
Order more with free return		.696	
Comfortable with returns			
More orders with return in store			.713
Check time before purchase			.651
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 4 iterations.			

Table 13 The first result of rotated component matrix

The KMO coefficient obtained in the second time is 0.629 (see Table 14), which is less than the first time but still greater than 0.6, and the variables pass Bartlett's Test of Sphericity again.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.629
Bartlett's Test of Sphericity	Approx. Chi-Square	291.220
	df	28
	Sig.	.000

Table 14 The second result of KMO and Bartlett's test

In the second analysis, the components with eigenvalues greater than 1 were extracted one more time. And these three factors explained 22.313%, 16.253% and 15.429% of the variance respectively, cumulatively explaining 53.995% of the variables, around 3% more than the first time (see Table 15).

Total Variance Explained									
Com-ponent	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.951	24.391	24.391	1.951	24.391	24.391	1.785	22.313	22.313
2	1.355	16.933	41.324	1.355	16.933	41.324	1.300	16.253	38.566

3	1.014	12.671	53.995	1.014	12.671	53.995	1.234	15.429	53.995
4	.912	11.402	65.397						
5	.862	10.770	76.167						
6	.709	8.866	85.033						
7	.634	7.922	92.955						
8	.564	7.045	100.000						

Extraction Method: Principal Component Analysis.

Table 15 The second result of total variance explained

As can be seen from the new rotation component matrix (see Table 16), all variables are divided into their respective components without conflict.

Rotated Component Matrix			
	Component		
	1	2	3
More returns with less effort	.736		
More returns with more options	.721		
More returns with longer period	.595		
Fewer returns if charged	.565		
Purchase items will be returned for free delivery		.837	
Order more with free returns		.742	
More orders if return in store			.690
Check time before purchase			.686
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. a. Rotation converged in 5 iterations.			

Table 16 The second result of rotated component matrix

Since the first component contains variables related to the change in the number of returns due to the leniency of the return policy, the first component is named "return policy"; the second component, free delivery and free returns, both promote repurchase behaviour beyond the original purchase intention of buyers, so the second component is named "additional purchase intention". The two variables in the third part do not appear to be correlated, but in terms of the deeper ideas that give rise to these two behaviours, the two have something in common. Preferring to shop at retailers that allow in-store returns indicates that this type of customer’s perceived risk is lower when dealing with this type of retailer, but higher when dealing with other retailers that do not offer in-store returns; the fact that one would check the return period before paying indicates that this type of customer would think that they have the possibility of returning the product in the future, implying uncertainty about the product, meaning that the perceived risk is higher for this type of customer. The third component is therefore called "perceived risk"

At this point the three factors can be represented by other variables, and the scores for each component are calculated as (see Table 17):

$$F1 = 0.319 \times V1 - 0.110 \times V2 - 0.067 \times V3 + 0.309 \times V4 + 0.033 \times V5 + 0.407 \times V6 + 0.041 \times V7 + 0.439 \times V8$$

$$F2 = -0.050 \times V1 + 0.567 \times V2 + 0.024 \times V3 + 0.021 \times V4 + 0.681 \times V5 - 0.055 \times V6 - 0.145 \times V7 - 0.007 \times V8$$

$$F3 = 0.037 \times V1 + 0.111 \times V2 + 0.560 \times V3 + 0.231 \times V4 - 0.219 \times V5 + 0.034 \times V6 + 0.583 \times V7 - 0.283 \times V8$$

Component Score Coefficient Matrix			
	Component		
	1	2	3
Fewer returns if charged (V1)	.319	-.050	.037
Order more with free returns (V2)	-.110	.567	.111
Check time before purchase (V3)	-.067	.024	.560
More returns with longer period (V4)	.309	.021	.231
Purchase items will be returned for free delivery (V5)	.033	.681	-.219
More returns with more options (V6)	.407	-.055	.034
More orders if return in store (V7)	.041	-.145	.583
More returns with less effort (V8)	.439	-.007	-.283
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.			

Table 17 Component Score Coefficient Matrix

4.6 Logistics regression analysis

Using the three new factors from the exploratory factor analysis as independent variables, and "returnmore" as the dependent variable in the logistic regression model, the results of the Hosmer and Lemeshow Test were first examined (see Table 18). The significance of 0.614 is greater than 0,05, indicating that the hypothesis that the logistic regression model is not well calibrated is rejected and the model is considered to be well calibrated, the model fit is good and the next model results are meaningful and plausible.

Hosmer and Lemeshow Test			
Step	Chi-square	df	Sig.
1	6.295	8	.614

Table 18 The result of Hosmer and Lemeshow Test

The final results were as follows (see Table 19). In comparison to the odds of the outcome occurring in the absence of a specific event, the odd ratio (OR) shows the likelihood that an outcome will occur given that occurrence , and is the ratio of the ratio of an event in a group to the ratio of that event within another group. (IBM, no date b). An event has higher chances of producing a particular result if the OR is larger than 1. The probability of that outcome happening are lower when the OR is smaller than 1, on the other hand (IBM, no date b). As can be seen from the table, the regression coefficients for lenient return policy, additional willingness to buy, and perceived risk are all greater than 0, indicating that all three positively influence the growth of returns during the epidemic, and the significance of all three independent variables is less than 0.05, indicating that there is no sufficient reason to reject hypotheses H1,H2, and H3.

For lenient return policy, the value of Exp(B), i.e. OR, is 1.302, implies that the change in the increase in more returns when the lenient return policy is increased by one unit is 1.302 times; for additional purchase intentions, the OR value is 1.462, implying that the change in the increase in more returns when the additional purchase intentions are increased by one unit is 1.462 times; for perceived risk, the OR value is 1.597, implying that the change in the increase in more returns when the perceived risk increases by one unit is 1.597 times, which has a slightly larger effect than that of either of the other two variables.

Variables in the Equation							
		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1a	REGR factor score 1 for analysis 3	.264	.114	5.337	1	.021	1.302
	REGR factor score 2 for analysis 3	.380	.125	9.271	1	.002	1.462
	REGR factor score 3 for analysis 3	.468	.117	15.911	1	.000	1.597
	Constant	-1.189	.116	104.722	1	.000	.304
a. Variable(s) entered on step 1: REGR factor score 1 for analysis 3, REGR factor score 2 for analysis 3, REGR factor score 3 for analysis 3.							

Table 19 The result of logistic regression

Chapter 5 Discussion

The data from the frequency distribution and the cross-tabulation of less return in-store and preferred way to return shows that although it was during the epidemic, wearing a mask did not cause people much trouble, or at least did not particularly influence people to return fashion goods in-store, and that the main reasons that influenced people to return fashion purchase offline were the distance to the shop, the remote location, the inconvenient opening times. People are most concerned with the attributes of the product itself, including size, quality, style and so on, with size being the most important concern. When asked what would make a return less likely, the majority of respondents chose "Better sizing chart", "Suggesting suitable sizes based on previous purchase " and "Photos of real customers wearing the item", all of which were about product size. However, this is a slight departure from the research of Kaushik *et al.* (2022). While Kaushik *et al.* (2022) also identified garment attributes as the number one category that influenced online apparel product returns, among the garment attributes of size, quality, colour and style, the results showed that having a defective product was the most significant factor influencing returns, with fit and size variation following behind. The explanation for such different results is that, on the one hand, it may be related to the different quality standards of the apparel industry in the different regions investigated, as the region of this study is in the UK, while the study of Kaushik *et al.* (2022) is in India; on the other hand, Kaushik *et al.* (2022) prioritised the factors influencing apparel returns through best-worst method, while this study is a direct reflection of customers' reasons for apparel returns through a questionnaire survey, and the difference in research methods may also contribute to the varying conclusions.

Therefore, it’s worth that fashion retailers will put more effort into the sizing of their merchandise, try to make clothes with the same set of size charts, try to give detailed size charts, and try to recommend more accurate sizes to their customers in order to make them return fewer items. Zheng, Favier and Huang (2012) also supported that fashion retailers can reduce customers’ perception risk through "3D images, details about garment sizes, material composition and product comparisons".

The hypotheses were not rejected and a lenient return policy, additional purchase intention, perceived risk would positively affect the volume of fashion product return. The more lenient the return policy, the greater the customer's willingness to add additional purchases to their original shopping plan as a result of the offer, the greater the perceived risk to customers of fashion goods, the more likely it is that the volume of fashion product returns will increase. For this, Gelbrich, Gäthke, and Hübner (2017) proposed that merchants may use retention incentives to strengthen traditional leniency policies, lowering customers' desire to return things while increasing their likelihood of repurchase. For example, when a customer keeps all the products in an order, the merchant could reward the customer by offering free delivery on the next order or by issuing a small coupon. The study (Gelbrich, Gäthke and Hübner, 2017) highlights the feasibility of this approach and shows that it can both significantly increase retention intentions and strengthen repurchase intentions. This is considered to be a valid recommendation that can be adopted by fashion retailers.

Chapter 6 Conclusion

The COVID-19 pandemic has not only caused physical harm to thousands of individuals, but has also taken a financial toll on retailers, especially fashion retailers. While the rise in retail sales has decreased, the rate of returns has risen.

This study used second hand survey data to help fashion retailers reduce the incidence of return behaviour. It first looked at customers' attitudes toward fashion returns and the characteristics of return behaviour from the customers' perspective. The frequency distributions in the descriptive analysis were used separately to examine respondents' demographic information, changes in the number of returns before and after the epidemic, their preferred way to return fashion purchases, the moment they regretted returning fashion products, and the reasons for returning fashion products, and cross-tabulation analysis was used to explore customers' behavioural characteristics, but only the cross-tabulation of the circumstances what will make respondents less likely to return fashion purchases in-store and their preferred way to return fashion products is significant. It was found that the most important reason for customers' returns was uncertainty about the clothing product, particularly uncertainty about clothing sizes. Exploratory factor analysis was then used twice to extract components, since the first time there was a variable that could not be divided into any of the factors, and the three primary factors that drove the increase in the number of fashion returns by customers during the pandemic were permissive return policies, increased eagerness to buy, and perceived risk. Finally, based on the findings of the investigation, some advice are made to fashion stores in order to lower the return rate.

This study has the following limitations. Firstly, the data used are secondary questionnaire data. In cases where the designer of the questionnaire is not the same person as the researcher who analysed it, there is often a discrepancy between the research direction of the analyst and the original design of the questionnaire, which ultimately results in the data used in the study not matching well and addressing the corresponding research questions. In addition to this, the scale questions in the questionnaire used in this study did not adequately refer to the established Likert scales from previous studies, and the number of scale questions was small and the number of multiple choice questions was high, resulting in the results of the reliability and validity tests of the questionnaire not being very good and allowing limited scope for analysis. The data used in future studies must match each other and the purpose of the study, and make full reference to the mature Likert scale, increase the number of scale questions and try to ensure the quality of the questionnaire. Secondly, the methods used in this study were mainly exploratory factor analysis and logistic regression, but this method has rarely been used in this area of research, with structural equation modelling and multiple linear regression used in most other studies. Thirdly, this study focuses on the fashion industry and the pandemic period; fourthly, this study does not discuss the mediating or moderating role of perceived risk.

List of References

Appriss (2022) *Consumer Returns in the Retail Industry 2021, Appriss Retail*. Available at: https://apprissretail.com/resource/2021-consumer-returns-in-the-retail-industry/ (Accessed: 19 August 2022).

Bartlett, J. (2014) 'The Hosmer-Lemeshow goodness of fit test for logistic regression', *The Stats Geek*, 16 February. Available at: https://thestatsgeek.com/2014/02/16/the-hosmer-lemeshow-goodness-of-fit-test-for-logistic-regression/ (Accessed: 29 September 2022).

Blázquez, M. (2014) 'Fashion Shopping in Multichannel Retail: The Role of Technology in Enhancing the Customer Experience', *International Journal of Electronic Commerce*, 18(4), pp. 97–116. Available at: https://doi.org/10.2753/JEC1086-4415180404.

Brydges, T. and Hanlon, M. (2020) 'Garment worker rights and the fashion industry's response to COVID-19', *Dialogues in Human Geography*, 10(2), pp. 195–198. Available at: https://doi.org/10.1177/2043820620933851.

Chen, B. and Chen, J. (2017) 'Compete in Price or Service?—A Study of Personalized Pricing and Money Back Guarantees', *Journal of Retailing*, 93(2), pp. 154–171. Available at: https://doi.org/10.1016/j.jretai.2016.12.005.

Chen, J. and Grewal, R. (2013) 'Competing in a supply chain via full-refund and no-refund customer returns policies', *International Journal of Production Economics*, 146(1), pp. 246–258. Available at: https://doi.org/10.1016/j.ijpe.2013.07.005.

Chen, W.-K., Chen, C.-W. and Lin, Y.-C. (2020) 'Understanding the influence of impulse buying toward consumers' post-purchase dissonance and return intention: an empirical investigation of apparel websites', *Journal of Ambient Intelligence and Humanized Computing* [Preprint]. Available at: https://doi.org/10.1007/s12652-020-02333-z.

Chueamuangphan, K., Kashyap, P. and Visvanathan, C. (2020) 'Packaging Waste from E-Commerce: Consumers' Awareness and Concern', in S.K. Ghosh (ed.) *Sustainable Waste Management: Policies and Case Studies*. Singapore: Springer, pp. 27–41. Available at: https://doi.org/10.1007/978-981-13-7071-7_3.

Cui, H., Rajagopalan, S. and Ward, A.R. (2020) 'Predicting product return volume using machine learning methods', *European Journal of Operational Research*, 281(3), pp. 612–627. Available at: https://doi.org/10.1016/j.ejor.2019.05.046.

Davis, S., Hagerty, M. and Gerstner, E. (1998) 'Return policies and the optimal level of "hassle"', *Journal of Economics and Business*, 50(5), pp. 445–460. Available at: https://doi.org/10.1016/S0148-6195(98)00013-7.

Dimoka, A., Hong, Y. and Pavlou, P.A. (2012) 'On Product Uncertainty in Online Markets: Theory and Evidence', *MIS Quarterly*, 36(2), pp. 395-A15. Available at: https://doi.org/10.2307/41703461.

Dowling, G.R. and Staelin, R. (1994) 'A Model of Perceived Risk and Intended Risk-handling Activity', *Journal of Consumer Research*, 21(1), pp. 119–134. Available at: https://doi.org/10.1086/209386.

Dowsett, S. (2020) *Clothes retailers need to decide on what to do with unsold stock | World Economic Forum*. Available at: https://www.weforum.org/agenda/2020/06/retailers-unsold-stock/ (Accessed: 28 September 2022).

Fu, Y. *et al.* (2016) 'Fused latent models for assessing product return propensity in online commerce', *Decision Support Systems*, 91, pp. 77–88. Available at: https://doi.org/10.1016/j.dss.2016.08.002.

Gelbrich, K., Gäthke, J. and Hübner, A. (2017) 'Rewarding customers who keep a product: How reinforcement affects customers' product return decision in online retailing', *Psychology & Marketing*, 34(9), pp. 853–867. Available at: https://doi.org/10.1002/mar.21027.

Goswami, S. and Chouhan, V. (2021) 'Impact of change in consumer behaviour and need prioritisation on retail industry in Rajasthan during COVID-19 pandemic', *Materials Today: Proceedings*, 46, pp. 10262–10267. Available at: https://doi.org/10.1016/j.matpr.2020.12.073.

Hassan, A.M. *et al.* (2006) 'Conceptualization and Measurement of Perceived Risk in Online Shopping', *Marketing Management Journal*, 16(1), pp. 138–147.

Hinton, P.R., McMurray, I. and Brownlow, C. (2014a) 'Chi-square test of independence and goodness of fit test', in *SPSS Explained*. 2nd edn. Routledge.

Hinton, P.R., McMurray, I. and Brownlow, C. (2014b) 'Using SPSS to analyse questionnaires: reliability', in *SPSS Explained*. 2nd edn. Routledge.

Hong, Y. (Kevin) and Pavlou, P.A. (2014) 'Product Fit Uncertainty in Online Markets: Nature, Effects, and Antecedents', *Information Systems Research*, 25(2), pp. 328–344. Available at: https://doi.org/10.1287/isre.2014.0520.

IBM (no date a) *About Linear Regression | IBM*. Available at: https://www.ibm.com/uk-en/topics/linear-regression#anchor-1853769488 (Accessed: 29 September 2022).

IBM (no date b) *What is Logistic regression? | IBM*. Available at: https://www.ibm.com/uk-en/topics/logistic-regression (Accessed: 29 September 2022).

Janakiraman, N. and Ordóñez, L. (2012) 'Effect of effort and deadlines on consumer product returns', *Journal of Consumer Psychology*, 22(2), pp. 260–271. Available at: https://doi.org/10.1016/j.jcps.2011.05.002.

Janakiraman, N., Syrdal, H.A. and Freling, R. (2016) 'The Effect of Return Policy Leniency on Consumer Purchase and Return Decisions: A Meta-analytic Review', *Journal of Retailing*, 92(2), pp. 226–235. Available at: https://doi.org/10.1016/j.jretai.2015.11.002.

Jeng, S.-P. (2017) 'Increasing customer purchase intention through product return policies: The pivotal impacts of retailer brand familiarity and product categories', *Journal of Retailing and Consumer Services*, 39, pp. 182–189. Available at: https://doi.org/10.1016/j.jretconser.2017.08.013.

Kaushik, V. *et al.* (2022) 'Modelling and prioritizing the factors for online apparel return using BWM approach', *Electronic Commerce Research*, 22(3), pp. 843–873.

King, T. and Dennis, C. (2006) 'Unethical consumers: Deshopping behaviour using the qualitative analysis of theory of planned behaviour and accompanied (de)shopping', *Qualitative Market Research: An International Journal*, 9(3), pp. 282–296. Available at: https://doi.org/10.1108/13522750610671699.

Kollewe, J. and Makortoff, K. (2022) 'Asos warns on profits amid "significant increase" in customer returns', *The Guardian*, 16 June. Available at: https://www.theguardian.com/business/2022/jun/16/asos-warns-on-profits-amid-significant-increase-in-customer-returns (Accessed: 19 August 2022).

Lantz, B. and Hjort, K. (2013) 'Real e-customer behavioural responses to free delivery and free returns', *Electronic Commerce Research*, 13(2), pp. 183–198. Available at: https://doi.org/10.1007/s10660-013-9125-0.

Lee, D.H. (2015) 'An Alternative Explanation of Consumer Product Returns from the Postpurchase Dissonance and Ecological Marketing Perspectives', *Psychology & Marketing*, 32(1), pp. 49–64. Available at: https://doi.org/10.1002/mar.20757.

Lepthien, A. (2019) 'Shipping fee schedules and return behavior', *Marketing Letters*, p. 15.

Lewis, M. (2006) 'The effect of shipping fees on customer acquisition, customer retention, and purchase quantities', *Journal of Retailing*, 82(1), pp. 13–23. Available at: https://doi.org/10.1016/j.jretai.2005.11.005.

Li, Y., Feng, C. and Liu, H. (2021) 'Package-Free Returns: A Trend in Green Ecommerce', in F.J. Martínez-López and D. López López (eds) *Advances in Digital Marketing and eCommerce*. Cham: Springer International Publishing (Springer Proceedings in Business and Economics), pp. 330–334. Available at: https://doi.org/10.1007/978-3-030-76520-0_34.

Lim, J. and Ayyagari, R. (2018) 'Investigating the determinants of telepresence in the e-commerce setting', *Computers in Human Behavior*, 85, pp. 360–371. Available at: https://doi.org/10.1016/j.chb.2018.04.024.

Lysenko-Ryba, K. and Zimon, D. (2021) 'Customer Behavioral Reactions to Negative Experiences during the Product Return', *Sustainability*, 13(2), p. 448. Available at: https://doi.org/10.3390/su13020448.

Mavlanova, T., Benbunan-Fich, R. and Koufaris, M. (2012) 'Signaling theory and information asymmetry in online commerce', *Information & Management*, 49(5), pp. 240–247. Available at: https://doi.org/10.1016/j.im.2012.05.004.

McHugh, M.L. (2013) 'The Chi-square test of independence', *Biochemia Medica*, 23(2), pp. 143–149. Available at: https://doi.org/10.11613/BM.2013.018.

Min, H., Ko, C.S. and Ko, H.J. (2006) 'The spatial and temporal consolidation of returned products in a closed-loop supply chain network', *Computers & Industrial Engineering*, 51(2), pp. 309–320. Available at: https://doi.org/10.1016/j.cie.2006.02.010.

Moroz, M. (2019) 'Tendency to Use the Virtual Fitting Room in Generation Y - Results of Qualitative Study', *Foundations of Management*, 11(1), pp. 239–254. Available at: https://doi.org/10.2478/fman-2019-0020.

OECD (2020) *E-commerce in the time of COVID-19*, *OECD*. Available at: https://www.oecd.org/coronavirus/policy-responses/e-commerce-in-the-time-of-covid-19-3a2b78e8/ (Accessed: 27 September 2022).

Oghazi, P. *et al.* (2018) 'Online purchase return policy leniency and purchase decision: Mediating role of consumer trust', *Journal of Retailing and Consumer Services*, 41, pp. 190–200. Available at: https://doi.org/10.1016/j.jretconser.2017.12.007.

Petersen, J.A. and Kumar, V. (2015) 'Perceived Risk, Product Returns, and Optimal Resource Allocation: Evidence from a Field Experiment', *Journal of Marketing Research*, 52(2), pp. 268–285. Available at: https://doi.org/10.1509/jmr.14.0174.

Pires, G., Stanton, J. and Eckford, A. (2004) 'Influences on the perceived risk of purchasing online', *Journal of Consumer Behaviour*, 4(2), pp. 118–131. Available at: https://doi.org/10.1002/cb.163.

Piron, F. and Young, M. (2000) 'Retail borrowing: insights and implications on returning used merchandise', *International Journal of Retail & Distribution Management*, 28(1), pp. 27–36. Available at: https://doi.org/10.1108/09590550010306755.

Powers, T.L. and Jack, E.P. (2013) 'The Influence of Cognitive Dissonance on Retail Product Returns', *Psychology & Marketing*, 30(8), pp. 724–735. Available at: https://doi.org/10.1002/mar.20640.

Powers, T.L. and Jack, E.P. (2015) 'Understanding the causes of retail product returns', *International Journal of Retail & Distribution Management*, 43(12), pp. 1182–1202. Available at: https://doi.org/10.1108/IJRDM-02-2014-0023.

Saunders, M., Lewis, P. and Thornhill, A. (2019) *Research Methods for Business Students*. Harlow, UNITED KINGDOM: Pearson Education, Limited. Available at: http://ebookcentral.proquest.com/lib/soton-ebooks/detail.action?docID=5774742 (Accessed: 28 August 2022).

Schiffer, J. (2019) *The unsustainable cost of free returns*, *Vogue Business*. Available at: https://www.voguebusiness.com/consumers/returns-rising-costs-retail-environmental (Accessed: 19 August 2022).

Schmidt, R.A. *et al.* (1999) 'Deshopping – the art of illicit consumption', *International Journal of Retail & Distribution Management*, 27(8), pp. 290–301. Available at: https://doi.org/10.1108/09590559910288569.

Sheth, J. (2020) 'Impact of Covid-19 on consumer behavior: Will the old habits return or die?', *Journal of Business Research*, 117, pp. 280–283. Available at: https://doi.org/10.1016/j.jbusres.2020.05.059.

Stock, J.R. and Mulki, J.P. (2009) 'Product Returns Processing: An Examination of Practices of Manufacturers, Wholesalers/Distributors, and Retailers', *Journal of Business Logistics*, 30(1), pp. 33–62. Available at: https://doi.org/10.1002/j.2158-1592.2009.tb00098.x.

Suwelack, T., Hogreve, J. and Hoyer, W.D. (2011) 'Understanding Money-Back Guarantees: Cognitive, Affective, and Behavioral Outcomes', *Journal of Retailing*, 87(4), pp. 462–478. Available at: https://doi.org/10.1016/j.jretai.2011.09.002.

Taherdoost, H. (2016) 'Validity and Reliability of the Research Instrument; How to Test the Validation of a Questionnaire/Survey in a Research'. Rochester, NY. Available at: https://doi.org/10.2139/ssrn.3205040.

Vivian Amasiatu, C. and Hussain Shah, M. (2014) 'First party fraud: a review of the forms and motives of fraudulent consumer behaviours in e-tailing', *International Journal of Retail & Distribution Management*, 42(9), pp. 805–817. Available at: https://doi.org/10.1108/IJRDM-05-2013-0112.

Wachter, K. *et al.* (2012) 'Exploring consumer orientation toward returns: unethical dimensions', *Business Ethics: A European Review*, 21(1), pp. 115–128. Available at: https://doi.org/10.1111/j.1467-8608.2011.01639.x.

Wang, M. and Qu, H. (2017) 'Review of the Research on the Impact of Online Shopping Return Policy on Consumer Behavior', *Journal of Business Administration Research*, 6(2), p. 15. Available at: https://doi.org/10.5430/jbar.v6n2p15.

Wang, Y. *et al.* (2019) 'The leniency of return policy and consumers' repurchase intention in online retailing', *Industrial Management & Data Systems*, 120(1), pp. 21–39. Available at: https://doi.org/10.1108/IMDS-01-2019-0016.

Wang, Y., Ramachandran, V. and Liu Sheng, O.R. (2021) 'Do Fit Opinions Matter? The Impact of Fit Context on Online Product Returns', *Information Systems Research*, 32(1), pp. 268–289. Available at: https://doi.org/10.1287/isre.2020.0965.

Yong A.G. and Pearce S. (2013) 'A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis', *Tutorials in Quantitative Methods for Psychology*, 09(2), pp. 79–94.

Zheng, L., Favier, M. and Huang, P. (2012) 'CHINESE CONSUMER PERCEIVED RISK AND RISK RELIEVERS IN E-SHOPPING FOR CLOTHING', 13(3), p. 20.

Zhu, Y. *et al.* (2018) 'A Local Algorithm for Product Return Prediction in E-Commerce', in, p. 3724. Available at: https://doi.org/10.24963/ijcai.2018/517.