Consumer Perspectives on Interventions to Combat Fraudulent Product Returns in Omnichannel Fashion Retail

Purpose:

The expansion of online shopping aligned with challenging economic conditions have contributed to increasing fraudulent retail product returns. Retailers employ numerous interventions typically determined by embedded perspectives within the company (supply side) rather than consumer-based assessments of their effectiveness (demand side). This study aims to understand how customers evaluate counter-fraud measures on opportunistic returns fraud in the UK. Based on the Fraud Triangle and the Theory of Planned Behaviour, we develop an empirically informed framework to assist retail practice.

Design/methodology/approach:

We collected 485 valid survey responses about consumer attitudes regarding which interventions are effective against different types of returns fraud. First, a principal component section evaluates the policies' effectiveness to identify any policy grouping that could help prioritise specific sets of policies. Second, cluster analysis follows a two-stage approach, where cluster size is determined, and then survey respondents are partitioned into subgroups based on how similar their beliefs are regarding the effectiveness of anti-fraud policies.

Findings:

We identify policies relating to perceived effectiveness of interventions and create customer profiles to assist retailers in conceptualising potential opportunistic fraudsters. Our product returns fraud framework adopts a consumer perspective to capture the perceived behavioural control of potential fraudsters. Results suggest effectiveness of different types of interventions vary between different types of consumers, which leads to the development of managerial implications to combat the fraud.

Originality/value:

This study is unique in assessing the perceived effectiveness of a range of interventions based on data collection and advanced analytics to combat fraudulent product returns in omnichannel retail.

Keywords: multichannel retail, omnichannel retail, product returns, returns fraud, returns policy.

1 Introduction

The escalating psychological and financial pressures increasingly evident in the post-pandemic cost-of-living crisis increase the temptation to gain financial benefits through improper means (Levi & Smith, 2021). In the retail sector, standard practices to extract benefits include theft and shoplifting but also extend to more impersonal, relatively easy, and non-violent ways like fraudulent product returns (Jolson, 1974). The National Retail Federation (NRF) reported that in the US, customers' returns accounted for 2023 around 14.5% of total sales, with a sizeable 13.7% of the returns being fraudulent (NRF, 2023). This represents a significant increase in fraudulent returns compared to 2020, where the average was 5.9%. Over just three years, the rate of fraudulent returns more than doubled, reflecting a 132.2% increase (NRF, 2020, 2023). Returns fraud cost US retailers $10.9 billion in 2015, soaring to a record-breaking $101 billion in 2024 (Shamiss, 2024). This sharp rise highlights the growing challenge of return fraud in retail, underscoring the need for enhanced fraud prevention strategies (Service Central, 2023). Fraudulent product returns are a seemingly victimless crime, with many offenders not even considering their actions illegitimate (Pei & Paswan, 2018). Product returns are not a new phenomenon, but they have increased considerably with the growth of online retailing and fierce price-based competition that ensures shipping fees remain low for consumers (Frei et al., 2023; Bernon et al., 2016). eCommerce has higher average returns rates than purchases made in-store[1], while high returns volumes and the complexity of omnichannel operations create many opportunities for fraudsters to abuse often-lenient returns policies (Shang et al., 2017; Hübner et al., 2016). Moreover, reverse logistics and returns processes are often tactical – the result of incremental changes over time, lacking strategic objectives (Hjort et al., 2019), which are particularly important when reverse logistics are outsourced (Russo et al., 2021).

[1] Customers' returns for 2023 in the US range between 17.6% for returns of goods purchased online and returned online and 10.02% for in-store returns exclusive of online purchases (NRF, 2023).

On the one hand, the prevalence of fraudulent return activities underlines the importance of robust returns policies and effective counter-fraud interventions. On the other hand, returns policies are crucial to customer service and satisfaction, enabling consumers to feel confident in their purchase decisions (Rokonuzzaman et al., 2021). Return policies also present unique challenges, as individuals exploit loopholes to engage in fraudulent practices, such as returning stolen or counterfeit goods for monetary gain. Consequently, retailers face financial losses, reduced profitability, and damaged brand reputation. Recognising these challenges, organisations have implemented interventions to mitigate fraudulent returns, including improved verification processes, leveraging data analytics to identify suspicious activity, for instance, across seemingly unrelated accounts, and related customer behaviour monitoring (Returnalyze, 2023). Nonetheless, the rapidly evolving nature of fraudulent activities poses ongoing challenges in the development of innovative strategies to safeguard retailers from this trend while also maintaining customer trust and loyalty. Based on the Fraud Act (The Crown Prosecution Service, 2006), we define fraudulent returns as being dishonest, intended to realise a gain and therefore result in a loss to retailers. The intention of the customer is an important factor; for instance, whether the item was purchased with the intention of using and returning it (which is called *wardrobing*). Changes of mind, or changing circumstances meaning an item is no longer needed, are legitimate within the generous returns policies of most retailers in Europe and North America.

Fraudulent returns are an increasing concern for retailers since the pandemic (Business Reporter, 2023; Zhang et al., 2023). The National Retail Federation's (2022) report suggests that for every $100 of accepted returns, there was a $10.30 loss because of returns fraud. Besides opportunistic fraudsters without a criminal history, there are serial returners (who often engage in wardrobing), organised crime and even professional refunding services that provide detailed instructions on how to defraud retailers and will even execute the fraudulent return for an agreed fee.

Although retailers and retail technology providers have implemented counter-fraud interventions (Zhang et al., 2023), they are usually driven by embedded retailer-specific needs and assumptions (representing the supply-side perspective) rather than being informed by consumer beliefs, attitudes, and behavioural responses (the demand side perspective). These interventions are particularly relevant when considering opportunistic fraud, rather than organised crime.

Rosenbaum et al. (2011) explored how consumers neutralise guilt when engaging in wardrobing and, on the contrary, what may lead them to exhibit restraint. Whilst this helps with understanding the emotional aspects of consumer fraud, it does not directly translate into actions retailers can take to influence consumer behaviour. Even if retailers can evaluate the effectiveness of certain interventions using statistical techniques, they likely benefit from learning about the perspectives of potential customers regarding counter-fraud interventions. Note that even though retailers could, in principle, evaluate counter-fraud interventions, these analyses require extensive and advanced analytical techniques that not all retailers have in-house. The results from a demand-oriented analysis offer valuable insights to assist retailers in complementing their decision-making and strategic behaviour to mitigate fraudulent activity.

This study aims to understand how customers evaluate counter-fraud measures on different types of opportunistic returns fraud in UK fashion retail. Therefore, our main research question is: How do consumers assess the effectiveness of anti-fraud interventions commonly implemented by fashion retailers? We use customers' quantitative assessments to identify a set of policies according to their perceived effectiveness and create profiles of customers that can assist retailers in understanding potential opportunistic fraudsters. This customer-centric approach complements studies which focused on the retailer perspective (Zhang et al., 2023). Together, they offer nuanced characterisations of mechanisms and contexts, focused on expanding knowledge of critical retail supply chain management problems. Our results reveal customer attitudes and beliefs about the effectiveness of a multidimensional set of interventions which could assist managers and practitioners in adapting their policies and strategies aimed at deterring and reducing fraudulent activities. The remainder of the paper is organised as follows: Section 2 presents the background and literature review, and Section 3 discusses the methodology, including the survey design, sample, and data collection. Section 4 discusses the empirical results, and Section 5 closes with conclusions and a final discussion.

2 Background, literature review and theoretical framing

Consumer-centric supply chain management spans four major functions (Esper et al., 2020): procurement, operations and manufacturing, logistics, and marketing, all of which are conducted with the goal of providing optimal service to consumers. Many of the product returns fraud challenges stem from this consumer-centric approach, which puts smooth returns processes above the need to protect the business from fraud. However, returns fraud inflicts losses on retailers, and counter-fraud interventions are increasingly necessary. This study provides insights into how such interventions are perceived, with implications on operations, logistics and marketing.

2.1 The diversity of returns fraud types

Returns fraud represents a persistent challenge for retailers in today's retail landscape. Numerous studies have identified different types of returns fraud. First, one particularly prominent area of investigation is *wardrobing*, which while not new (Cole, 1989), has become increasingly socially acceptable (Jack et al., 2019). It involves customers purchasing a product, utilising it, and subsequently returning it to obtain a full refund (Shang et al., 2017; Phau et al., 2022). UK retailers are said to lose up to £1.5 billion annually due to wardrobing behaviour (Checkpoint Systems, 2019). 40% of retailers observed an increase in wardrobing practices in the period from 2018 to 2019, with 44% citing notable impacts on their profit margins due to returns handling and packaging expenses (Rosenthal, 2019). The National Retail Federation (NRF, 2023) estimates that almost 50% of US retailers experienced wardrobing in 2023. Although wardrobing is typically associated with clothing purchases (King & Dennis, 2003), it also occurs with other merchandise, such as big-screen televisions for sporting events, air conditioning units, and children's bikes during the summer holidays (Altug et al., 2021).

Second, fraudulent returns, where consumers *intentionally damage products* or falsely imply there is a manufacturing defect to obtain a full refund, present significant challenges to retailers similar to those encountered in addressing wardrobing (Harris, 2008) and also abuse retailer return policies and regulations (Chang & Guo, 2021). This type of fraud involves deceptive practices by consumers, making it difficult for retailers to differentiate between genuine product defects and intentional damage.

Third, the prevalence of online shopping and flexible returns options has led to an increase in *price arbitrage* as a distinct form of returns fraud, which encompasses various deceptive tactics. For instance, a high-value product is purchased, a refund is requested, yet the original packaging is returned containing the genuine item missing an expensive component, a counterfeit item, a random item of similar weight, or nothing at all (Speights & Hilinski, 2005; Droms, 2013). A notable real-world example is the alleged case of a 22-year-old individual defrauding Amazon for approximately $370,000 by returning packages filled with dirt instead of the actual goods (Moynihan & Aguiar, 2019). One of the challenges in combating price arbitrage fraud is the lack of item-level identification of products (Zhang et al., 2023): without this, retailers are unable to determine whether the returned item was legitimately sold or if it matches the correct product.

Fourth, *returning stolen products* is a common form of in-store returns fraud, with Kang and Johnson (2009) revealing that nearly 95% of retailers were impacted by such deception. These items may have been stolen either from the retailer itself or elsewhere, with the aim of obtaining a refund or store credit (Piron & Young, 2000). The detection of stolen items during the returns process can be difficult, particularly when the retailer lacks adequate item-level identification systems.

2.2 Return policies and counter-fraud interventions

The prevalence of fraudulent return activities highlights the imperative of implementing resilient returns policies, which play a crucial role in shaping customer purchase decisions (Petersen & Kumar, 2009). However, lenient policies could inadvertently foster fraudulent behaviour among certain customers (e.g., Piron & Young, 2000; Chen et al., 2023). As both Harris (2010) and King & Dennis (2006) highlighted, dishonest customers exploit lenient return policies because they know there are limited consequences for their deceptive actions. Research has explored the adoption of returns policies featuring various restrictions, but these lack a systematic or consistent approach. In this study, we bundle return policies and interventions into three categories based on the nature of their effectiveness for different returns fraud types (policies that create barriers, evoke monetary implications, and punitive measures) and address three categories of the returns fraud management framework (Zhang et al., 2023): Deterrence & Prevention; Detection; and Mitigation.

2.2.1 Creating barriers by increasing efforts and difficulties of returning (Deterrence & Prevention)

Restrictive return policies effectively discourage fraudulent behaviour (Chang & Yang, 2022). Barriers to returning include mandating the provision of purchase receipts, introducing account registration procedures, and utilising specific return desks for processing returns (Frei et al., 2020; Zhang et al., 2023). Reducing returns windows (Röllecke et al., 2018; Shang et al., 2019) may discourage fraudulent returns, especially wardrobing (Ishfaq et al., 2016; Janakiraman et al., 2016; d'Astous & Guèvremont, 2008). For instance, evidence indicates that customer returns (for any reason) within 90 days of purchase were valued at approximately $100 billion annually in the USA (Ardeshirilajimi & Azadivar, 2015). Offering shorter return windows not only allows retailers to restock products more quickly but also mitigates product value losses (Frei et al., 2020).

The return effort reflects the extent to which consumers must adhere to specific criteria when returning. This may involve maintaining the product's original tags/labels and packaging, completing forms, or needing to visit a returns desk for in-store returns (Zhang et al., 2023). More rigorous return policies aim to cause inconvenience to returns fraudsters (Heiman et al., 2001). Requesting customers retain original receipts can reduce the likelihood of returning stolen items; incentivising customers to register as members can furnish retailers with enhanced information for returns data analysis to identify unusual return behaviour; retaining product labels or tags attached to well-visible locations serves to mitigate the probability of wardrobing.

2.2.2 Monetary implications in returns policies (Deterrence & Prevention)

Returns policies aimed at recovering some of the costs of the returns and deterring fraudulent returns include applying restocking fees (Akturk et al., 2021; Shang et al., 2017), providing only partial refunds on returned items (Heiman et al., 2001), and imposing shipping fees. Fast fashion retailer, Zara pioneered the introduction of returns fees in the UK, with many other retailers subsequently following, including in North America. Chu et al. (1998) found that offering a partial refund without questioning customers' reasons for return is an effective approach for handling abusive returns, particularly when the salvage value of the returned product is sufficiently high. Akturk et al. (2021) demonstrated that the imposition of a restocking fee by retailers can significantly reduce returns fraud. Other monetary restrictions include exchange-only or store credit policies. It is plausible that these monetary measures deter wardrobing fraud (Zhang et al., 2023), but the degree to which customers perceive these measures to be effective is unclear.

2.2.3 Punitive measures (Detection and Mitigation)

Along with the implementation of technologies and systems to enhance fraud detection and prevention, punitive measures can be effective. They include disabling the accounts of serial returners (Akturk et al., 2021) and issuing cautionary emails (Robertson et al., 2020). The effectiveness of these measures relies on the integration of innovative technologies and systems in product return processes and operations, facilitating the accumulation of relevant data. Noteworthy examples of such technologies include QR return codes derived from blockchain-based systems and the obligatory registration of accounts for return requests (Shen et al., 2022). Leveraging the collected data, retailers can analyse customer purchase and return records to identify patterns of returns abuse, allowing them to restrict future purchases and returns. Customer profiling can be used to prevent opportunistic as well as serial fraudulent activities. For instance, ASOS has introduced the measure to block individuals exhibiting recurrent behavioural patterns involving purchasing clothes in bulk and requesting refunds, one presumes after wearing them (Young, 2019). In the store environment, the use of CCTV increases the visibility of customers and allows fraudulent behaviours to be detected and recorded, therefore also serving as a highly visible deterrent, increasing awareness of risks among potential wrongdoers (Zhang et al., 2023).

2.3 Theoretical framing

Pellathy et al. (2018) pointed out that Middle-Range Theorising (Stank et al., 2017; Craighead et at., 2024) is particularly suitable for explaining an observed outcome (fraudulent returns behaviour) based on a mechanism considered in its context (consumer perceptions in fashion retail in the UK). Consumer returns fraud corresponds to one of the identified critical areas in logistics consumer service, in particular revealing the role of human and behavioural factors (Stank et al., 2017). We explore how opportunistic consumer decision-making is influenced by retailer counter-fraud measures, and link this to behavioural norms that create the social context within which decision-making and potential fraud action occur.

To understand the mechanisms behind opportunistic fraudulent behaviour in fashion retail, we apply the Theory of Planned Behaviour (TPB; Ajzen, 1991), a psychological framework. TPB has been extensively applied across various domains, including social psychology, environmental psychology, and the study of fraud (King & Dennis, 2006; Wang et al., 2013; Rozenkowska, 2023). TPB identifies three primary factors that influence an individual's behaviour: attitudes, subjective norms, and perceived behavioural control (Ajzen, 2002). For example, King et al. (2008) is the first study using the TPB to examine dishonest consumer return behaviours through a survey of 535 female consumers. Their findings indicated that perceiving dishonest returns as easy or enjoyable increases the likelihood of engaging in such behaviour. In the context of fraudulent returns, such as wardrobing, it is plausible that if an individual believes the benefits of engaging in wardrobing outweigh the potential costs (e.g., time, effort), they are more likely to participate in such activities. Similarly, if wardrobing is perceived as socially acceptable, customers are more likely to perform this act, as they feel less pressure from social norms and expectations. Concerning behavioural control, stricter return policies can influence consumer perceptions of their ability to commit fraudulent returns. The more challenging the return process, or the higher the costs associated with returning, the less capable consumers feel they are of engaging in such behaviour, thereby reducing their intention to do so. Johnson & Rhee (2008) emphasised that complicated or costly return procedures diminish opportunistic return behaviours.

Furthermore, the Fraud Triangle (Cressey, 1953; Schuchter & Levi, 2016) offers additional insights into our understanding of returns fraud. This theoretical framework is extensively applied to analyse why individuals violate trust and engage in fraudulent activities (Homer, 2020; Piron & Young, 2000) and includes three critical factors — pressure, opportunity, and rationalization — that motivate fraudsters to commit crimes (Cressey, 1973). Organisations frequently use this model to assess their vulnerability to fraud and to devise preventative strategies (Homer, 2020). Particularly in financially challenging times, people experience economic and psychological pressure that can increase the likelihood of them committing fraud. Opportunities arise for instance when retailers have weaknesses in their returns systems, at the level of policies and their implementation as well as in their software and communication systems. Omnichannel retailers can be particularly vulnerable when it comes to the coordination and synchronisation of information between their channels (Zhang et al., 2023).

The rationalisation aspect in the Fraud Triangle refers to the need for potential fraudsters to justify their actions to themselves. This is easier when committing a seemingly victimless crime, such as returns fraud.

Cognitive Appraisal Theory (Bagozzi, 1992) can shed further light onto rationalisation and moral justification of fraudulent consumer behaviour. This is illustrated in Masorgo et al. (2023) demonstrating how delivery driver behaviour can influence customer outcomes, such as satisfaction with the retailer and repurchase intentions. It is shown that details of the interactions with the retailer (or their proxy, a contracted logistics company) can create an emotional response that is then transferred onto the satisfaction with the purchase itself. Similarly, it is plausible that the emotional aspect of the interactions with the retailer or their logistics partner could influence a consumer's decision to engage in a fraudulent behaviour.

The augmented version of the Fraud Triangle (Schuchter & Levi, 2016) includes the aspect of capability, which implies that returns fraud is more likely to happen when people have ways to execute it. Social media and wider online portals play a role in this by communicating insights and tricks for executing returns fraud, alongside the availability of fraudulent refunder services (Frank on Fraud, 2022).

As such, from the retailer's perspective, both the TPB and the (augmented) Fraud Triangle emphasise the importance of perceived behavioural control and opportunity in curbing returns fraud. This is illustrated in the multi-channel product returns fraud framework (Figure 1) proposed in Zhang et al. (2023), which suggests four categories of factors driving returns fraud:

First, external factors stem from the environment in which retailers and consumers operate, such as laws and regulation as well as the economic conditions in a country. Second, product-related factors refer to the fact that, for instance, small but expensive products are much more fraud-prone than others. The third category, retailer related factors, offers by far the most opportunities for improvements and interventions to reduce opportunities for fraudulent returns, which is the focus of Zhang et al. (2023). Fourth, consumer-related factors reflect on individual consumer situations and are mostly beyond the influence of retailers.

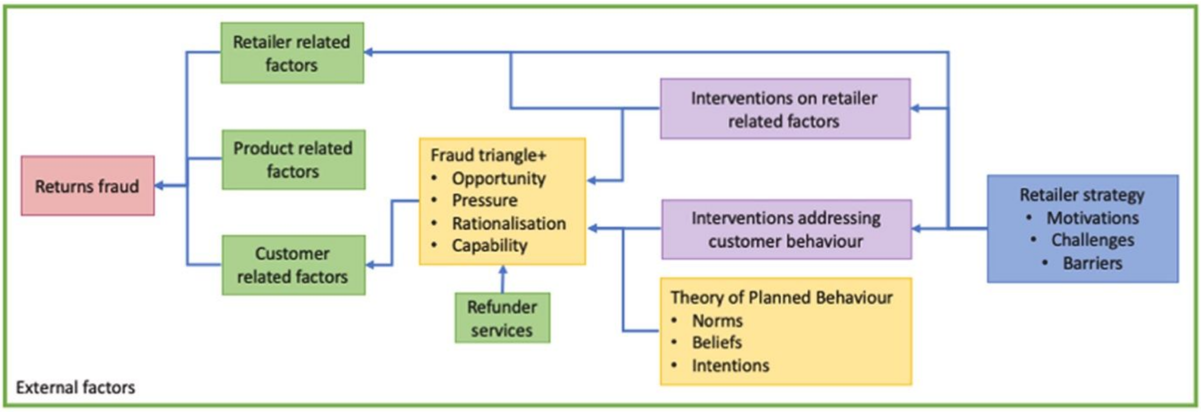


Figure 1: The multi-channel product returns fraud framework (Zhang et al., 2023), used with permission

Many retailers are adopting stricter policies to reduce and deter fraudulent activities (Zhang et al., 2023). These strategies include implementing shorter return windows, issuing warning messages, and banning serial returners, all aimed at making fraudulent returns more challenging and less attractive to fraudsters. However, there is a gap in understanding how individual consumers assess these new strategies in terms of effort, opportunities, and effectiveness. As these evaluations shape the expectations of potential fraudsters, affecting their perceived behavioural control, this knowledge is essential for fine-tuning approaches to effectively reduce fraud.

2.4 Research gaps and the rationale of the study

The studies discussed above offer insights into different counter-fraud interventions that involve amendments to returns policies aimed at mitigating return fraud behaviour. However, assessments of the effectiveness of these interventions remain limited in scale and scope. Striking a balance between facilitating straightforward and timely returns for legitimate customers while also discouraging fraudulent practices is critical (Zhang et al., 2023). Therefore, this exploratory study aims to understand how customers evaluate the effectiveness of counter-fraud interventions on different types of returns fraud. The findings of this study can provide valuable insights for retailers in refining their strategies. Based on the above review and theoretical framing, we contend that different policies would be applied for various purposes, depending on the type of fraudulent behaviour and expected effects. However, there is a lack of evidence regarding the effectiveness of these policies. Certain counter-fraud interventions will likely yield varying degrees of efficacy in preventing distinct types of fraudulent and problematic returns. Particularly, specific *combinations of interventions* may more effectively tackle certain forms of returns fraud. Exploring this is the goal of this study. Table A summarises two pertinent research streams (product returns and fraudulent product returns) along with the research gaps this study tackles.

Table A: Literature and research gaps

Literature	Selected references	Topic	Research gap	Contribution
Product returns studies that focus on customer attitudes and perceptions	Jones et al. (2024); Frei et al. (2023); Russo et al., (2022); Pei & Paswan (2018)	a) Customer perception of fairness in returns decisions; b) Implications of product returns on retailer operations	Customer and potential opportunistic fraudsters perspective on fraudulent product returns	Conceptual framework to characterise the roles of customers in returns fraud and attitudes of potential opportunistic fraudsters
Returns fraud and mitigation strategies from the retailer's perspective	Shang et al. (2017); Zhang et al. (2023)	a) Factors that enable fraudulent returns; b) Strategies for retailers to combat product returns fraud in a multichannel environment	Customer-specific factors not considered; lack of quantitative evidence on customer attitudes, beliefs, and perceptions regarding the effectiveness of anti-fraud interventions	Survey evidence with a comprehensive assessment of fraud types and mitigation strategies: Retailers can use customer segmentation to customise their counter-fraud measures

3 Methodology

3.1 Survey design

We elicited consumer beliefs and attitudes via an anonymous online survey. We designed a questionnaire to identify UK customer evaluations of nine counter-fraud interventions, detailed in Table B, addressing four categories of fraudulent behaviour in omnichannel retail: wardrobing, damaged product returns, price arbitrage, and stolen items returns. For each fraud category, a scenario was formulated, introducing a brief description outlining how unscrupulous customers engage in each type of behaviour. Subsequently, respondents were asked to evaluate the overall effectiveness of the interventions (see, Table B) in discouraging the described fraudulent activities. The interventions examined under each scenario are grounded in the returns fraud management framework (Zhang et al., 2023), introduced in Section 2.2.

Table B : Explored counter-fraud interventions

Interventions category	**Specific counter-fraud interventions**
Creating barriers	• Shorter returns windows • Requiring proof of purchase • Return registration procedures • Specific returns desks
Creating monetary disadvantages	• Restocking fees or shipping fees • Issuing partial refunds • Exchanges or store credit only
Punitive measures	• Banning serial returners(*) based on data collection and analytics • Banning shoplifting fraudsters with CCTV support

(*) Serial returning in itself is not fraud, but it is problematic for retailers and often linked to wardrobing and other forms of returns fraud.

3.2 Sample and Data Collection

518 participants in the UK were recruited from the leading online behavioural research platform, Prolific. The platform provides access to reliable and large-scale data collection by connecting researchers with vetted participants, including representative samples from the UK and the US in some research designs. Responses from Prolific participants have been shown to provide significantly higher data quality on measures like attention, honesty, comprehension, and reliability than those from other well-known platforms (Peer et al., 2017; Peer et al., 2022).

Eligibility criteria for the non-probabilistic sample included UK residency, age 18 or over, and having an average Prolific approval rating equal to or greater than 95% from their previous studies. As described in detail in Section 4.1 below and presented in Table D, the demographic distribution of our sample resembles the UK population in terms of gender but is slightly younger than the overall distribution in the UK. The final sample is, therefore, more relevant to our study, given that we want to elicit beliefs from individuals who have been more exposed to omnichannel retailers themselves, and it is known that online shoppers tend to be relatively younger (Swinyard & Smith, 2003).

Each participant received £1.20 for participating in the study, which is consistent with a £9 hourly rate as the average completion time was 8 minutes. To further improve the reliability of our results, an instructional manipulation check (IMC) was placed in the middle of the survey to detect inattentive participants (Oppenheimer et al., 2009). A total of 18 participants failed the IMC and were therefore excluded from the sample. An additional 15 participants were excluded for providing invalid answers (e.g., straight-lining), insufficient data, or exceeding the response time threshold of 30 minutes. Consequently, the final sample incorporated 485 respondents. Our statistical results are robust and consistent when analysing the entire sample and are not driven by additional data or quality filters.

3.3 Measurements

Due to the ethical considerations and the sensitivity around fraudulent consumer behaviour, the participants were not asked to declare their engagement in fraudulent activities. Instead, an indirect approach was adopted to evaluate the policies against fraudulent consumer behaviour in fashion retail, where each of the fraud phenomena was first explained to the participants, followed by a set of measures that they were invited to score. Furthermore, participants identifiable information was also not recorded for the purpose of the study. The full set of questions and measurements can be found in Table C.

Table C: Data Description

Constructs	**Variables**				**Scale**
Control Variables	Age				Interval
	Gender				Female/Male/ Other
	Familiarity with fraudulent behaviour (knowing people who have done this)				Ordinal (6 categories)
Items/Construct	**Wardrobing**	**Damaged Fraud**	**Price Arbitrage**	**Return Stolen Item**	**Scale**

Shorter return period	✓	✓	✓	✗	0-100
Return via the customer service desk	✓	✓	✗	✓	0-100
Return labels request	✓	✓	✓	✗	0-100
Return with tags still attached	✓	✓	✓	✓	0-100
Return shipping fee payment	✓	✓	✓	✗	0-100
Exchange or refund onto a gift card.	✓	✓	✓	✓	0-100
Mandatory account registration	✓	✓	✓	✗	0-100
Banning serial returners	✓	✓	✓	✗	0-100
Option to rent items	✓	✗	✗	✗	5-point Likert scale
Option to buy the same or a similar but used item for a much lower price	✓	✗	✗	✗	5-point Likert scale
Purchase receipt requirement	✗	✗	✓	✗	0-100
CCTV coverage	✗	✗	✗	✓	0-100
Return forms with full information	✗	✗	✗	✓	0-100

3.3 Data analysis

Considering the exploratory nature of this study, the primary objective of the data collection was to identify patterns in the evaluation of policies, and across different types of fraudulent behaviour, by the participants. As a result, these data were processed starting with the descriptive analysis, which comprised two stages.

In the first stage, the characteristics of the respondents were reviewed, and their mean evaluations of the measures were considered. Given the possible dependency of the samples (where the same respondents were asked to evaluate different measures in relation to different types of fraudulent behaviour) and the potential lack of homogeneity in the evaluations, the comparisons were made using distribution-free (non-parametric) statistical methods. These provide more robust estimates compared to parametric methods under such conditions, as they do not assume any particular type of distribution (Lee et al., 2013).

In the second stage of descriptive analysis, the evaluations of policy effectiveness were further scrutinised with the aim of identifying any 'bundles' that could help categorise the measures and account for any mutual correlations. This is achieved through exploratory principal component analysis, based on the assumption that some groupings are possible where the combined items (measures) represent the underlying 'core' policy (Kerlinger, 1986). This method is also treated as a conventional procedure towards capturing the behavioural constructs, which are often latent, following a multi-item approach (Nunnally, 1978; Dobni, 2008).

At the next step, the focus was diverted to the participants themselves as consumers, thus potentially exhibiting fraudulent behaviour. Therefore, the respondents were explored by means of cluster analysis with the aim to identify any groups that depict similar evaluations of particular policies – a widely adopted technique in market research to customer profiling (Higuchi & Maehara, 2021).

4 Results

4.1 Descriptive analysis

Table D provides descriptive statistics of our sample. The participants are evenly split between male and female, with the majority falling into the category of under 45 years old, whereas 36% of the total number of participants are above this age. 43% of respondents are familiar with individuals who have engaged in returns-related fraudulent behaviour. We also provide descriptive statistics for England and Wales from the Office of National Statistics (ONS, 2022). The demographic distribution of our samples resembles the UK population in terms of gender and includes a slightly younger selection of individuals than the overall distribution in the UK.

Participants evaluated the proposed measures for each type of fraudulent behaviour among consumers in the fashion industry: wardrobing, price arbitrage, damaged item return and stolen item return. Friedman's test for dependent samples indicates statistically significant differences (Chi-Square 40.933, $p<0.001$) in mean ranks of the evaluations across the four types of fraudulent behaviour, suggesting differences in perceived policy effectiveness across different types of fraud. The preliminary analysis (Appendix 1) further suggests that some of the evaluations are significantly correlated with each other, where individuals score particular policies as high or low, more or less consistently across different types of fraudulent behaviour.

Table D: Sample description

Variables		**Sample (%)**	**England and Wales (%)**
Gender			
	Female	49.9	**51.0**
	Male	49.3	**49.0**
	Other	0.8	-
Age			
	18-24	20.0	**10**
	25-34	23.1	**17**
	35-44	20.8	**17**
	45-54	13.4	**16**
	55-64	10.9	**16**
	65 and over	11.8	**24**
Familiarity with fraudulent behaviour			
	I do not know people who have done this	57.1	-
	I know people who have done this once	20.6	-
	I know people who have done this a couple of times	18.4	-
	I know people who have done this regularly	3.9	-

Table E examines reported beliefs about the effectiveness of policies across fraud types, where the mean evaluation scores are presented for each policy. The colour scale displays policies from most effective (darker) to least effective (lighter). Shorter return period, customer desk returns, and requiring requesting return labels, on average demonstrated the lowest effectiveness (with scores under 50% considered to be as relatively ineffective). Returns with tags still attached, exchange/refund onto a gift card, and banning serial returners scored considerably high across all types of fraudulent behaviours. The only exceptions were returns with the refund on a gift card for price arbitrage and stolen items and, returns with the tags still attached for stolen items. Tags are deemed the most effective policy against all types of fraudulent behaviour except for stolen item returns. Banning and CCTV are evaluated highly across the board, while mandatory account registration is believed to be effective against stolen item returns. Appendix 2 displays the evaluations along with standard deviations in brackets, where it is found that dispersion around the mean also remains highly consistent across the different policies and fraud types.

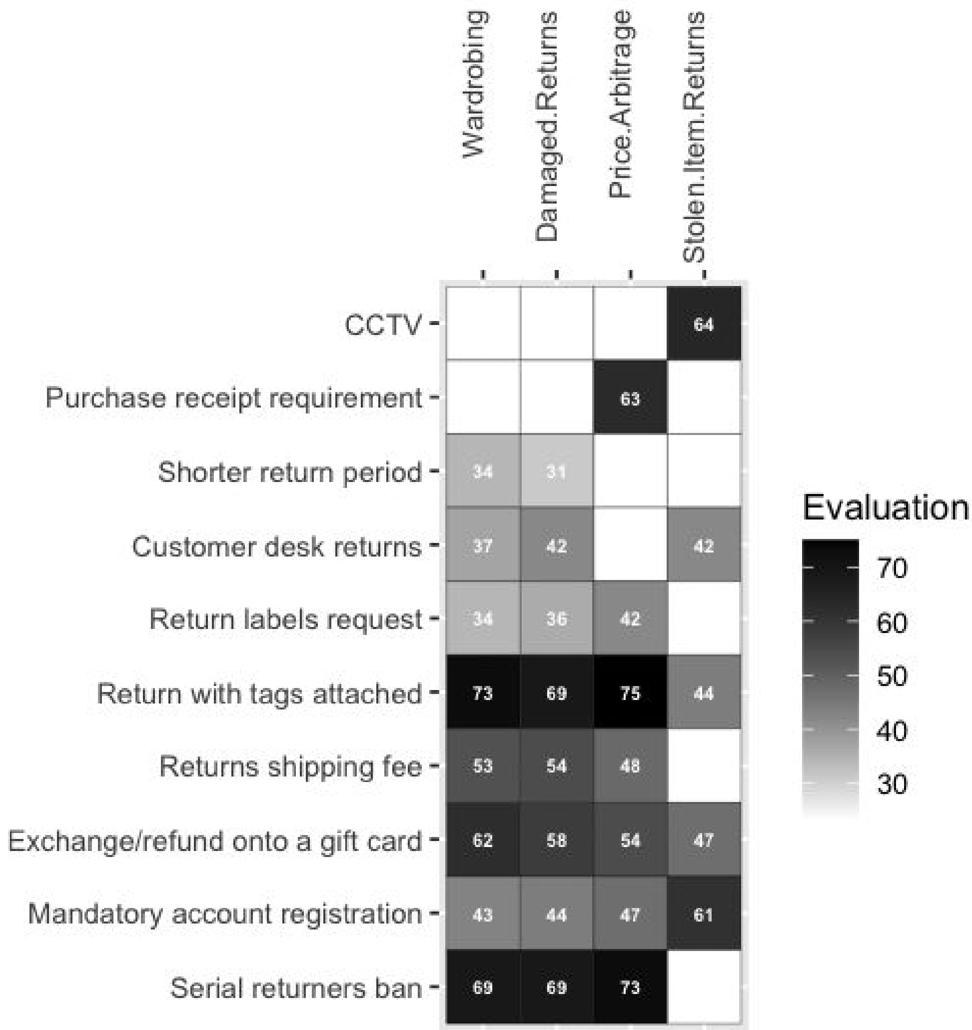
Considering the correlations among the evaluations, as well as the patterns revealed above, an exploratory principal component analysis was performed to understand the dimensionality of the proposed set of measures and identify any measures that stand alone (Howard, 2023). This method allows us to explore the extent to which the policies are replaceable with one another in addition to analysing their potential effectiveness. It also permits the assessment of potential combinations of policies, with such analysis likely to aid further development of policies and their tailoring to particular types of fraudulent behaviour.

A standard procedure based on Cattell (1965) was used, exploring multiple extraction methods, and eliminating policies with the minimum contribution to a potential component (a set of policies) to achieve a solution which could be further interpretable[2]. Principal component extraction and varimax rotation were applied, where the final results were reduced to the components (sets of policies) presented in Table F for each type of fraudulent behaviour.

To illustrate how components also capture the distributional dimension of the different policies, Figure 2 plots the kernel density estimate for shorter return periods (Component 1) and returns with tags attached (Component 3) for the case of wardrobing. The components successfully manage to segment policies by the expected level of effectiveness. For completeness, Appendix B shows all the kernel densities for the distribution of policy effectiveness across components (Appendix B columns) and fraud types (Appendix B rows). With few exceptions, components are very efficient at identifying clusters of interventions with similar expected effectiveness (within component variation) and isolating the variability across components (between component variation).

Table E: Mean evaluation scores of policy effectiveness across different returns fraud types

[2] Cattell (1965) validated this method quantitatively, whereas Goretzko et al. (2021) used this method interpretatively in an exploratory context, as it is done in this study.



The method developed by Hair et al. (1998) was followed to make decisions about the inclusion of the policies into components. This approach considers the contribution of systematic variance, filtering out large partial correlations in comparison to the sum of the correlations (where the communalities should be greater than 0.5). The number of components was further determined based on the eigenvalues and further evaluated in terms of their reliability (where the policies reducing the reliability of the component were discarded). The acceptable range of Cronbach's Alpha as the measure of reliability is maintained from 0.5 as the aim of the analysis is not to maximise the internal consistency of the measures within a policy set but to explore patterns that combine different measures, noting the 'stand-alone' measures on par with others (Frazier & Rody, 1991; Bonett & Wright, 2015; Chan & Idris, 2017).

High measures of sampling adequacy (Keiser-Meyer-Olkin measure of 0.75 and above) and the significance of Bartlett's Test of Sphericity ($p<0.01$) ensure the prerequisite for the principal component analysis to be meaningful in capturing the correlations identified previously. As a result, the policies have been logically loaded into the components (forming sets of policies) with a few inconsistencies noted below. A descriptive title was given to each component to represent the nature of the proposed set of policies.

Table F: Exploratory principal component analysis by the type of fraudulent behaviour

Wardrobing							
Components			**M**	**SD**	**Factor loading**	**% of variance**	**A***
	Component 1: creating barriers					23.75	0.58
		Shorter return period	33.67	24.87	0.753		
		Customer desk returns	36.83	28.49	0.635		
		Return labels request	34.37	26.33	0.735		
	Component 2: monetary disadvantage					23.44	0.62
		Returns shipping fee	53.47	29.33	0.747		
		Exchange/refund onto a gift card	61.68	28.97	0.821		
	Component 3: creating barriers/punitive measures					17.21	0.36
		Return with tags attached	72.88	25.58	0.864		
		Banning serial returners	68.74	27.84	0.543		
Damaged Returns							
Components			**M**	**SD**	**Factor loading**	**% of variance**	**A***
	Component 1: creating barriers					27.21	0.69
		Shorter return period	30.95	25.06	0.591		
		Customer desk returns	41.6	28.24	0.503		
		Return labels request	35.86	25.78	0.285		
	Component 2: monetary disadvantage/creating barriers/punitive measures					33.28	0.75
		Returns shipping fee	53.54	29.80	0.730		
		Exchange/refund onto a gift card	57.72	29.36	0.683		
		Mandatory account registration	43.78	30.87	0.737		

		Banning serial returners	69.34	27.41	0.585		
Price arbitrage							
Components			**M**	**SD**	**Factor loading**	**% of variance**	**A***
	Component 1: creating barriers					29.76	0.62
		Return with tags attached	75.47	25.88	0.896		
		Purchase receipt requirement	62.79	31.12	0.761		
	Component 2: monetary disadvantage/creating barriers					43.18	0.80
		Return labels request	41.61	29.16	0.842		
		Returns shipping fee	47.88	30.21	0.816		
		Mandatory account registration	47.41	31.78	0.813		
Stolen item returns							
Components			**M**	**SD**	**Factor loading**	**% of variance**	**A***
	Component 1: monetary disadvantage/creating barriers					65.75	0.74
		Customer desk returns	41.86	30.44	0.810		
		Return with tags attached	44.12	35.00	0.842		
		Exchange/refund onto a gift card	46.96	31.08	0.779		

**Reliability (Cronbach's Alpha value)*

For wardrobing, three components were extracted, with the third component still being maintained, despite a low value of Cronbach's Alpha, for interpretation purposes and to avoid one-item components as per the Scree test (Cattell, 1965). Two components were formed for damaged item returns and price arbitrage fraudulent behaviour, and one – for stolen item returns[3].

Broadly, the distinguished components fall into the following categories: policies creating barriers for fraudulent returns (shorter return period, customer desk returns, return labels

[3] Cattell (1965) states that components must be formed of more than one item. However, based on the data, it is possible to have multiple components (comprised of multiple items/their combinations) - the more components are derived, the more 'diverse' the items are (the more differences can be found among them/their combinations).

request, return with tags attached, purchase receipt requirement, and mandatory account registration); policies creating monetary disadvantage (return shipping fee payment, refund onto the gift card), and punitive measures that imply certain consequences for offenders (banning serial returners and CCTV).

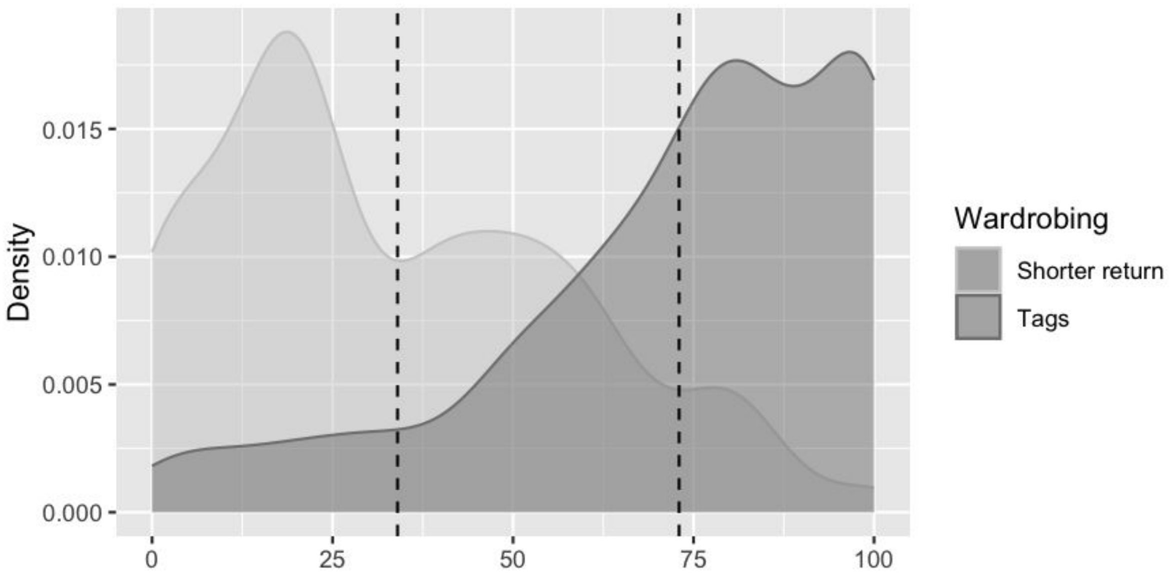


Figure 2: Kernel density estimate for shorter return periods (Component 1) and returns with tags attached (Component 3) for wardrobing

** Vertical lines display mean evaluation for shorter return periods (left) and returns with tags attached (right). See Table F for details.*

Specifically, for wardrobing, 'creating barriers' policies appear to be considered ineffective, policies creating monetary disadvantage are regarded as moderately effective, whereas tags (as a creating barriers policy) and banning (as a punitive policy) are thought of as most effective. For damaged returns, the same three 'creating barriers' measures are evaluated as ineffective, while punitive and creating monetary disadvantage measures in combination with mandatory registration are deemed moderately effective. Notably, 'creating barriers' measures (tags and receipts) are thought of as effective in combatting price arbitrage, and only mandatory registration and CCTV are standalone policies that are seen as effective for stolen item returns. Banning serial returns also appears to be an effective standalone policy across most types of fraudulent behaviour, while mandatory registration appears to be a non-effective standalone policy (apart from stolen item returns, where it is effective).

Considering the variances across the evaluations of effectiveness and the differences across the different types of fraudulent behaviour, further analysis was conducted to determine homogeneous groups of participants (in terms of their policies evaluation patterns) through exploratory cluster analysis to propose a more refined set of measures.

4.2 Exploratory cluster analysis

To identify a set of descriptive clusters or subgroups based on respondent evaluation of policies, unsupervised learning methods have been applied to our data. In the first stage, for each type of fraudulent behaviour, hierarchical cluster analysis was used to establish an adequate number of clusters which group the individuals who are similar in terms of their evaluation of the policies (Saunders, 1980). This was achieved by reviewing the dendrogram[4] (see Appendix 4) and exploring the combinations of clustering solutions to balance among maximising the Euclidean distance between the clusters, reducing variance within the clusters, and maintaining enough participants within each group (Punj & Stewart, 1983). At each stage, the retrieved cluster results were reviewed in terms of the composition of evaluations of policies. Subsequently, by applying K-means cluster analysis the sample is divided into the determined number of clusters (groups), each of which is characterised by a different mean level of evaluation for the policies (Higuchi & Maehara, 2021).

The classification of the respondents based on their evaluation of policies to combat wardrobing fraudulent behaviour is summarised in Table G. The largest group (Cluster 3) is represented by the individuals who find policies creating monetary disadvantage, tags mandatory registration, and banning (as a punitive measure) most significant. This cluster is dominated by male respondents aged under 44. The smallest group (Cluster 1) is made up of

[4] A dendrogram is a tree-like graphical representation of all the observations constructed through a prespecified dissimilarity measure between each pair of data points.

mostly female participants, mostly under the age of 34 who consider none of the policies effective, apart from tags. This is further balanced by Cluster 2 (demographically comparable to Cluster 3), which finds tags, gift card refunds and banning as moderately effective.

Table G: K-means cluster analysis of respondents based on their evaluations of policies against wardrobing

Wardrobing	**Cluster 1**	**Cluster 2**	**Cluster 3**
Mean Evaluation Scores across policies			
Shorter return period	33	23	42
Customer desk returns	37	19	49
Return labels request	33	16	48
Return with tags attached	77	60	81
Returns shipping fee	23	45	71
Exchange/refund onto a gift card	24	62	77
Mandatory account registration	37	22	60
Serial returners ban	45	65	81
Gender (mode value)	Female	Male	Male
Age (mode value)	25-34	25-34	35-44
Familiarity with fraudulent behaviour (mode value)	I do not know people who have done this	I do not know people who have done this	I do not know people who have done this
Number of cases	91	166	228

**Mean evaluations over 50% are highlighted in dark grey, 33-50% - in moderate grey, and under 33% - in light grey.*

***The differences in median evaluations are significant across the three clusters (Kruskal-Wallis Test, 5% significance level).*

As wardrobing fraudulent behaviour is the most frequently observed (or suspected) in the fashion retail industry (Speights & Hilinski, 2005), two options to tackle this type of fraud were separately offered for participant evaluation: an opportunity to rent the item instead of buying it (referred below as option 1)[5], and an opportunity to buy the same or similar used item (referred below as option 2)[6]. **Error! Reference source not found.** shows that just over 50% of respondents consider these options as likely to reduce wardrobing fraudulent behaviour, almost equally splitting the sample (58% and 56.3% of participants evaluate provided options as 'somewhat' or 'extremely' likely effective).

Table H: Frequencies for evaluations of additional options to reduce wardrobing fraudulent behaviour

	Option 1: renting items	Option 2: buy the same or a similar used item
Extremely unlikely	5.4	3.7
Somewhat unlikely	21.6	21.6
Neither likely nor unlikely	15.1	18.4
Somewhat likely	49.1	46.4
Extremely likely	8.9	9.9
Total	**100**	**100**

Table H further relates the two additional options to the type of cluster that was identified. Although the results suggest an even split between the opinions for Cluster 2, there is a dominance in negative anticipations for Clusters 1 and 3. However, no statistically significant relationship between belonging to a particular cluster and the likelihood of the options to reduce wardrobing fraudulent behaviour was detected (Chi-Square, $p<0.05$).

Table H: The observed frequencies for the classification of respondents and the likelihood of reducing wardrobing fraudulent behaviour through each of the two options

	Likely to reduce wardrobing fraudulent behaviour	Unlikely to reduce wardrobing fraudulent behaviour

[5] The question is: "Imagine people of your age and gender who have engaged in wardrobing behaviour: If there was **an option to rent items**, do you think they would opt for this option instead of wardrobing?"
[6] Imagine people of your age and gender who have engaged in wardrobing behaviour: If there was **an option to buy the same or a similar but used item** for a much lower price, do you think they would opt for this option instead of wardrobing?

	Option 1: renting items	Option 2: buy the same or a similar used item	Option 1: renting items	Option 2: buy the same or a similar used item
Cluster 1	35	38	56	53
Cluster 2	81	79	85	87
Cluster 3	88	95	140	133
Total	**204**	**212**	**281**	**273**

The results in Table I for damaged item returns policies similarly suggest three clusters of individuals. Cluster 3 (equally split between women and men, and mostly presented by 25-44 and over 65 individuals) comprises participants who find all policies effective, apart from shorter return periods. Respondents in Cluster 2, represented mainly by men under the age of 34, evaluate creating monetary disadvantage measures, tags and banning as the most effective. Cluster 1 is very similar in profile and composition to the same cluster (Cluster 1) formed for wardrobing fraudulent behaviour, where all policies apart from tags are evaluated as ineffective.

Table I: K-means cluster analysis of respondents based on their evaluations of policies against damaged returns fraudulent behaviour

Damaged returns	**Cluster 1**	**Cluster 2**	**Cluster 3**
Mean Evaluation Scores across policies			
Shorter return period	22	22	47
Customer desk returns	27	34	60
Return labels request	19	26	59
Return with tags attached	51	67	85
Returns shipping fee	21	59	73
Exchange/refund onto a gift card	26	66	75
Mandatory account registration	19	38	69
Serial returners ban	48	72	83
Gender (mode value)	Female	Male	Female/Male
Age (mode value)	18-24	25-34	35-44
Familiarity with fraudulent behaviour (mode value)	I do not know people who have done this	I do not know people who have done this	I do not know people who have done this
Number of cases	136	174	175

**Mean evaluations over 50% are highlighted in dark grey, 33-50% - in moderate grey, and under 33% - in light grey.*

***The differences in median evaluations are significant across the three clusters (Kruskal-Wallis Test, 5% significance level).*

Replicating the analysis for price arbitrage in Table J yields similar results. Cluster 3 is identical to Cluster 3 for damaged item returns, being also close in composition to Cluster 3 for wardrobing behaviour, where all policies are evaluated as effective, apart from shorter return period. Cluster 1, this time mostly represented by men, suggests an opposite profile, where all the policies are deemed as ineffective or moderately effective (in the case of banning and tags). While Cluster 2 balances the previous two (represented by predominantly women unlike in the previous two cases), suggesting tags, receipts and banning as the most effective ones.

Table J: K-means cluster analysis of respondents based on their evaluations of policies against price arbitrage fraudulent behaviour

Price Arbitrage	**Cluster 1**	**Cluster 2**	**Cluster 3**
Mean Evaluation Scores across policies			
Shorter return period	14	17	36
Return with tags attached	57	87	82
Purchase receipt requirement	28	80	78
Return labels request	21	28	68
Returns shipping fee	30	36	72
Exchange/refund onto a gift card	35	54	70
Mandatory account registration	26	35	74
Serial returners ban	55	74	86
Gender (mode value)	Male	Female	Female
Age (mode value)	18-24	25-34	35-44
Familiarity with fraudulent behaviour (mode value)	I do not know people who have done this	I know people who have done this at least once	I do not know people who have done this
Number of cases	152	143	190

**Mean evaluations over 50% are highlighted in dark grey, 33-50% - in moderate grey, and under 33% - in light grey.*

***The differences in median evaluations are significant across the three clusters (Kruskal-Wallis Test, 5% significance level).*

In Table K, another set of participants is classified based on their evaluations of policies against stolen item returns. Cluster 3, as in the previous two cases, is formed from mostly women within the 25-44 and over 65 age groups, who tend to evaluate all policies as effective. On the other side, Cluster 1 is predominantly represented by female participants under 44 years old who find none of the policies effective apart from CCTV (with a very minor impact). Cluster 2 sits in the middle and is comprised of mostly men younger than 44 years old who find CCTV, mandatory account registration and exchange onto a gift card as reasonably effective policies.

Table K: K-means cluster analysis of respondents based on their evaluations of policies against stolen items return fraudulent behaviour

Stolen Items Return	Cluster 1	Cluster 2	Cluster 3
Mean Evaluation Scores across policies			
CCTV	52	65	78
Customer desk returns	15	46	76
Return with tags attached	12	47	87
Exchange/refund onto a gift card	20	54	74
Mandatory account registration	40	65	83
Gender (mode value)	Female	Male	Female
Age (mode value)	18-34	25-34	35-44
Familiarity with fraudulent behaviour (mode value)	I do not know people who have done this	I do not know people who have done this	I do not know people who have done this
Number of cases	168	206	111

**Mean evaluations over 50% are highlighted in dark grey, 33-50% - in moderate grey, and under 33% - in light grey.*

***The differences in median evaluations are significant across the three clusters (Kruskal-Wallis Test, 5% significance level).*

Further to the analysis above, the groupings were compared pairwise with each other (through cross tabulation), where significant associations were determined (Chi-Square, p< 0.01) across all types of fraudulent behaviour. In other words, the respondents appear to fall into the same Cluster group (ranked from 1 to 3 as per the increasing number of effective policies) on each occasion. As a result, three distinct groups of participants (as potential consumers in the fashion industry) are distinguished:

1. **Optimists**: Those who find most policies effective (except for a shorter return period), regardless of the type of fraudulent behaviour, are mostly represented by women under the age of 44 years (apart from the evaluations of wardrobing behaviour where the proportion of men in the sample marginally exceeds the proportion of women, 51% versus 49%). Also, slight differences are manifested in the evaluations of measures against wardrobing behaviour, where customer desk returns and returns requiring a label request are also deemed ineffective.

2. **Pessimists**: Those who evaluate all policies as ineffective with the exception of tags (where it is deemed to be effective in all cases but stolen item returns), represented mainly by women (apart from price arbitrage evaluations) under 44 years old (with the most frequent category of younger individuals aged 18-24). There are slight deviations as per the type of fraudulent behaviour, where banning and CCTV are also deemed as potentially effective for price arbitrage and stolen item returns.

3. **Pragmatists**: The most diverse group of individuals, demonstrating different evaluations across different types of fraudulent behaviour, predominantly represented by men below the age of 54 years old with those aged 25-34 being the most frequent category (with the exception of price arbitrage, where women prevail). Within this category, individuals find at least one of the monetary disadvantage policies as effective, punitive measures as effective, and most of the 'creating barriers' measures as ineffective.

Following the proposed sets of policies, the effectiveness of various measures could be further classified per type of fraudulent behaviour:

1. **Wardrobing:**

Almost all participants regard tags effective when tackling this type of fraudulent behaviour, as a standalone measure. The majority of the respondents also evaluate the rest of the 'creating barriers measures' as ineffective (there is an exception of mandatory registration as a standalone measure deemed effective by Optimists). Banning (as a standalone punitive measure) and monetary disadvantage measures are deemed effective by optimists and pragmatists.

2. **Damaged item returns:**

Tags, once more, are found to be an effective standalone measure by all types of participants on par with banning. The rest of the bundled 'creating barriers' measures are deemed ineffective by all groups apart from optimists, who also score mandatory registration as effective (yet, demonstrating a moderate effect). Monetary disadvantage measures and banning (as a punitive measure) are evaluated as effective by both pragmatists and optimists.

3. **Price arbitrage:**

As before, all participants evaluated tags as an effective measure in this case, too, while a shorter return period is considered as ineffective. Some differences were evident for the rest of the 'creating barriers' measures, where the purchase receipt requirement is found effective by pragmatists and optimists, while mandatory registration and return with labels are also favoured by optimists. Monetary disadvantage measures, while positively evaluated by optimists, are not so useful in the eyes of pragmatists, who only find the exchange into a gift card marginally effective.

4. **Stolen item returns:**

CCTV is considered to be effective by all participants as a standalone measure to reduce the return of stolen items. Creating barriers measures are only evaluated as effective by optimists, who also highly score mandatory registration. Monetary disadvantage measure (exchange onto a gift card) is deemed moderately effective by pragmatists and viewed favourably by optimists who find all other measures equally successful.

5 Discussion, conceptual framework, and conclusions

With increasing economic pressure on consumers, retailers are reporting a strong increase in “shrink”, an umbrella term for various losses (Peacock, 2023). A significant proportion of such “shrink” is known to be retail crime, including fraudulent returns. This is a challenge because some return fraud types are notoriously difficult to measure and differentiate from legal but unwanted behaviour; particularly, wardrobing versus serial ordering and returning for the thrill of trying on new items. Social media play a significant role in making such behaviours seemingly socially acceptable (Phau et al., 2022). Younger people are frequent users of social media, making them the most frequently suspected wardrobers. At the same time, the novel and evolving nature of returns fraud exposes retailers to unidentified loopholes in their delivery and return policies. For instance, most returns policies currently do not communicate that serial returning may lead to the account being suspended.

5.1 Towards a conceptual framework for counter-fraud interventions in omnichannel product returns

The multichannel product returns fraud framework (Zhang et al., 2023) focuses on factors under the control of the retailer, which this study takes as a basis. We use empirical data to validate it and provide additional details relating to the consumer's side. The results show that understanding consumer attitudes and beliefs regarding counter-fraud opportunities offers potential for retailers to optimise their strategies for reducing both unwanted and fraudulent consumer behaviour. Following our analysis, Figure 3 presents an augmented conceptual framework for product returns fraud that incorporates the perspectives of consumers and retailers.

The framework illustrates the interaction between the supply side (retailers) and the demand side (consumers). In this market interaction, opportunistic fraudsters could potentially engage in four main categories of product returns fraud: wardrobing, damaged product returns, price arbitrage, and stolen items returns. Given the evolving nature of returns fraudulent behaviour, we include additional or new fraud types under the "Others" category into the framework. While we acknowledge that organised crime is often involved in product return fraud operations, we focus our study and framework on the individual and non-organised components: opportunistic fraudulent consumer behaviour.

At the same time, retailers implement policies and strategies in the form of interventions to mitigate fraudulent returns as they impact companies' bottom line. Following the product returns fraud framework (Zhang et al., 2023), we identify nine primary counter-fraud interventions, which can be further classified into three main categories: creating barriers, creating monetary disadvantages, and punitive measures.

In this study, we focus on connecting the consumer perspective on the effectiveness of specific counter-fraud interventions. The Fraud Triangle (Cressey, 1953), or rather its augmented version (Schuchter & Levi, 2016), indicates four factors that decide whether fraud will be committed: *opportunity, pressure, rationalisation, and capability*. Weaknesses in retailers' returns systems provide consumers with opportunities to commit fraud, which they are more likely to do when under economic pressure. Both the rationalisation and the capability aspects are influenced by social media, where consumers are given ideas and easy tricks for "stretching" or abusing returns policies and it is suggested that this is acceptable behaviour.

The Theory of Planned Behaviour (Ajzen, 1991) helps us further understand customer rationalisation of the fraud action. *Attitudes and social norms* are influenced by what others consider acceptable or desirable, including wardrobing and gaining financial benefits from tricking "faceless" retailers.

The results of our study show the context for the development of *perceived behavioural control* among potential fraudsters. For instance, more punitive measures are deemed to be more effective, while depending on the type of the customers, others might be more or less effective.

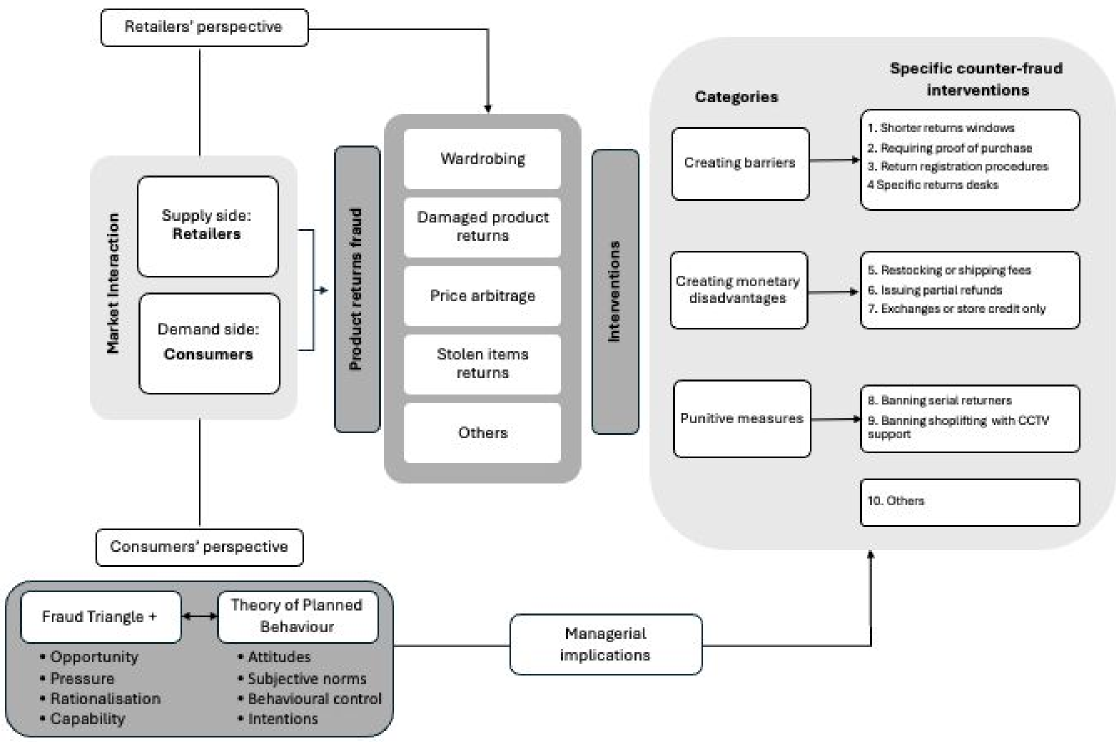


Figure 3: Conceptual framework for counter-fraud interventions in omnichannel product returns

Zooming out, the theoretical implications of these findings relate to consumer-centric supply chain management and the functions involved in addressing returns fraud (Esper et al., 2020), namely operations, logistics, and marketing, and their mutual interfaces. Data analytics and information management play key roles in returns fraud prevention in which retailers can identify and flag potential fraudsters by analysing customer history, including behavioural patterns and account information. For instance, fraudsters may use multiple accounts that can be linked to each other through geographical details. Retailers can use such information in fraud deterrence, prevention, detection and mitigation, creating the image of being tough on fraud through targeted marketing. However, most customer-centric retailers acknowledge that introducing stricter policies often increases the complexities of returns for honest consumers, thus creating a non-straightforward decision problem for retailers. In line with Esper et al. (2020), data mining at the interface of marketing, logistics, and operations can be used to gain a detailed understanding of consumer perceptions and attitudes regarding policies and fraudulent behaviour. Retailers must ultimately evaluate the trade-off between prioritising customers' experience and satisfaction and adopting effective strategies and policies for fraud prevention. In the next section, we provide data-driven implications that can guide the decision process for managers and practitioners in retail. They will be most effective if used in conjunction with retailer and market specific data analytics.

5.2 Managerial implications

Retailers lack scientific evidence to inform and assist them in creating effective strategies to combat returns fraud. This study contributes to filling this gap by providing data-driven evidence from a consumer perspective by exploring attitudes about the effectiveness of a series of counter-fraud interventions addressing Deterrence and Prevention, Detection, and Mitigation (Zhang et al., 2023). Based on the analysis of consumer survey data, we develop a series of recommendations and guidance for managers around the perceived effectiveness of the different policy types, detailed in Table M. The implications of # 1-3 provide more general insights for managers.

To capture the variations in a wider population of potential customers within the fashion industry, we further develop managerial implications # 4-7 for addressing each form of fraudulent behaviour considered in this study. The variations in perception are based on the exploratory cluster analysis results, which reflects the diversity of individuals within a relatively homogeneous group of survey respondents in the UK. As a result, the assumption of “one size fits all” could be inadequate when considering the effectiveness of counter-fraud policies.

Table M: Managerial implications

#	Managerial implication
1	Policies that create barriers, such as shorter returns windows, customer desk returns, and return label requests (except for tags; details in # 4-6), appear to be mostly ineffective for all four forms of fraudulent returns.
2	Data analytics of potential customers' profiles should be used with monetary barriers, as are they are perceived as effective against all four forms of returns fraud.
3	Implementing punitive measures are perceived as most effective against customers returning damaged or stolen goods.
4	Retailers affected by wardrobing behaviour should evaluate tags and related innovations, as consumers perceive them as mostly effective. Similarly, banning fraudsters and monetary disadvantage measures should be effective if implemented along with analytics on potential customers' profiles.
5	Retailers affected by damaged item returns should consider tags and banning policies, as consumers perceive them as mostly effective. Using monetary disadvantage measures could be effective, but they need retailer-specific analytics on potential customers' profiles.
6	Retailers affected by price arbitrage behaviour should use tags and related innovations, as consumers perceive them as mostly effective. The purchase receipt requirement and gift card exchanges could be effective if implemented along with analytics on potential customers' profiles.
7	Retailers affected by stolen item returns should use CCTV technologies, as consumers perceive them as mostly effective. Monetary disadvantage measures could be effective if implemented along with analytics on potential customers' profiles.

Retailers should recognise that policies aiming at reducing fraud partially overlap with policies targeting genuine product returns. For instance, reducing returns windows may not be very effective against fraudulent returns, but it can be useful for managing genuine returns (Shang et al., 2019). From a managerial point of view, we recommend that retailers design clear action plans identifying the strategies that aim at each type of returns and then analyse overlaps and possible contradictions. Moreover, retailers should maximise the use of data analytics to tailor policies depending on specific retail sectors and demographics of potential customers.

Although the study does not target retail fraud 'offenders' directly, it is revealed that individuals have very different perceptions of counter-fraud interventions, and therefore it is worthwhile for the retailers to tackle returns fraud by recognising the heterogeneity of types and profiles of consumers.

5.3 Limitations of this study and future work

This study develops a method to elicit beliefs regarding the perceived efficacy of interventions to combat fraudulent product returns in omnichannel fashion retail. It is clear that limitations remain. Future research could address the proxy nature of the study, where, due to ethical considerations, the *opinions* of survey respondents were solicited to capture the perspective of opportunistic fraudsters. It would be relevant for future studies to query a sample of committed fraudsters on what influences their behaviour, though this is undoubtedly ethically challenging to achieve. Alternatively, there is the opportunity for retailers and academics to collaborate in real-world experiments to provide data on returns fraud before and after the implementation of specific counter-fraud measures to identify their relative efficacy.

It is likely that customer behaviours will vary between different retailers. Therefore, it could be advantageous for retailers to monitor and profile customers in relation to return activities. Such a database would allow for an informative segmentation of customers, where the managerial implication provided in Section 5.2 could be tested and an examination of the effects of the interventions in real-life scenarios. Further work is also needed to explore what kind of information retailers must provide to consumers regarding their measures for Deterrence & Prevention, Detection, and Mitigation, and in which form.

Linked with the variegated nature of our sample of consumers, we speculate that the application of Cognitive Appraisal Theory (as discussed in 2.3) to opportunistic returns fraud could be an avenue for further research to explore, for example, why pessimists consider all (most of the) interventions as ineffective, or why pragmatists could be more prone to rationalisation of the fraudulent behaviour. At the same time, the presence of pessimists suggests the positive effect of perceived behavioural control on potential fraudulent behaviour, potentially offering an encouragement of such a behaviour.

The results of this study could be used by retailers in combination with their in-house insights and individual policies on how to target fraudsters from the firm perspective (as opposed to the consumer perspective). As such, this study makes a valuable step in indicating the perceived effectiveness of different combinations of counter-fraud measures from the demand side to assist retailers in further understanding consumer perceptions and encouraging further research in the area.

Investments into technology are necessary to further reduce fraud opportunities in retail operations and supply chains, and the managerial implications resulting from this study can provide guidance in selecting the most effective tools. For instance, modern video surveillance (managerial implication #7) with item level identification can be very effective against any fraud involving elements of theft as well as claims that certain (valuable) items were not included in a parcel. Additionally, item level identification tags (managerial implications #4-6) are effective in preventing various fraud types such as price arbitrage. Tags that also contain temperature and movement sensors can both prevent wardrobing and increase supply chain traceability. Further research should delve into how retail supply chains can effectively leverage these advanced technologies and optimised operations to mitigate fraud risks, considering both the technical and operational challenges of implementing these solutions. Our framework and research propositions provide a robust foundation for future studies, allowing scholars to expand the understanding of how investments in these technologies can be strategically aligned with broader supply chain goals, using the five-step Middle-Range Theory approach outlined by Craighead et al. (2024). By incorporating these elements into future research, there is significant potential to contribute to the broader field of supply chain management, addressing not just fraud prevention but also improving overall efficiency and transparency.

Acknowledgements

This research was funded by the UK Economics and Social Research Council (reference ES/V015605/1) and supported by the ECR Retail Loss Group.

References

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.

Ajzen, I. (2002). *Constructing a TPB questionnaire: Conceptual and methodological considerations*. Available online: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=0574b20bd58130dd5a961f1a2db10fd1fcbae95d [Accessed on 01 April 2024]

Akturk, M. S., Ketzenberg, M., & Yıldız, B. (2021). Managing consumer returns with technology-enabled countermeasures. *Omega*, 102, 102337.

Altug, M. S., Aydinliyim, T., & Jain, A. (2021). Managing opportunistic consumer returns in retail operations. *Management Science*, 67(9), 5660-5678.

Ardeshirilajimi, A., & Azadivar, F. (2015). Reverse supply chain plan for remanufacturing commercial returns. *The International Journal of Advanced Manufacturing Technology*, 77, 1767-1779.

Bernon M, Cullen J, Gorst J (2016) Online retail returns management. *International Journal of Physical Distribution & Logistics Management*, 46(6/7):584-605.

Bagozzi, R. P. (1992). The self-regulation of attitudes, intentions, and behavior. *Social Psychology Quarterly*, 55(2), 178–204. https://doi.org/10.2307/2786945

Bonett, D. G., & Wright, T. A. (2015). Cronbach's Alpha Reliability: Interval Estimation, Hypothesis Testing, and Sample Size Planning. *Journal of Organizational Behavior*, 36, 3-15.

Business Reporter (2023). *Fighting return fraud*. Available online: https://www.business-reporter.co.uk/retail/fighting-return-fraud (Accessed 2 Oct 2023)

Cattell, R.B. (1965). "Factor analysis: an introduction to essentials: The purpose and underlying models", *Biometrics*, 21(1), pp. 190-215.

Chan, L.L. & Idris, N. (2017). "Validity and reliability of the instrument using exploratory factor analysis and Cronbach's alpha". *International Journal of Academic Research in Business and Social Sciences*, 7(10), pp.400-410.

Chang, H. H., & Guo, Y. Y. (2021). Online fraudulent returns in Taiwan: The impacts of e-retailers' transaction ethics and consumer personality. *Journal of Retailing and Consumer Services*, *61*, 102529. https://doi.org/10.1016/j.jretconser.2021.102529

Chang, H. H., & Yang, T. S. (2022). Consumer rights or unethical behaviors: Exploring the impacts of retailer return policies. *Journal of Retailing and Consumer Services*, 64, 102779. https://doi.org/10.1016/j.jretconser.2021.102779

Checkpoint Systems (2019). *Wardrobing - The Facts every retailer needs to know*. Retrieved from: https://checkpointsystems.com/uk/reports/wardrobing/ (Accessed on 06 June 2022).

Chen, J., Yu, B., Chen, B., & Liu, Z. (2023). Lenient vs. stringent returns policies in the presence of fraudulent returns: The role of customers' fairness perceptions. *Omega*, *117*, 102843. https://doi.org/10.1016/j.omega.2023.102843

Chu, W., Gerstner, E., & Hess, J. D. (1998). Managing dissatisfaction: How to decrease customer opportunism by partial refunds. *Journal of Service Research*, *1*(2), 140-155.

Cole, C. A. (1989). Deterrence and consumer fraud. *Journal of Retailing*, *65*(1), 107.

Craighead, C. W., Cheng, L., & Ketchen Jr, D. J. (2024). Using middle-range theorizing to advance supply chain management research: A how-to primer and demonstration. Journal of Business Logistics, 45(3), e12381.

Cressey, D.R., 1953. *Other People's Money: A Study in the Social Psychology of Embezzlement.* The Free Press, Glencoe, IL.

Cressey, D. R., & Moore, C. A. (1983). Managerial values and corporate codes of ethics. *California Management Review*, 25(4), 53-77.

Dobni, C.B. (2008). "Measuring innovation culture in organisations: The development of a generalised innovation culture construct using exploratory factor analysis", *European Journal of Innovation Management*, 11(4), pp. 539-559.

d'Astous, A., & Guèvremont, A. (2008). Effects of retailer post-purchase guarantee policies on consumer perceptions with the moderating influence of financial risk and product complexity. *Journal of Retailing and Consumer Services*, 15(4), 306-314.

Droms, C. M. (2013). Take it back: the impact of dynamic consumer goals in return and exchange interactions. *Services Marketing Quarterly*, *34*(1), 67-85. ttps://doi.org/10.1080/15332969.2013.739944

Esper, T.L., Castillo, V.E., Ren, K., Sodero, A., Wan, X., Croxton, K.L., Knemeyer, A.M., DeNunzio, S., Zinn, W. and Goldsby, T.J. (2020), Everything Old is New Again: The Age of Consumer-Centric Supply Chain Management. Journal of Business Logistics, 41, 286-293

Frank on Fraud (2022). Report – There Are Now Over 1,600 Refund Fraud Companies. Available at: https://frankonfraud.com/fraud-trends/report-there-are-now-over-1600-refund-fraud-companies/

Frazier, G., & Rody, R. (1991), "The use of influence strategies in inter-firm relationships in industrial product channels", *Journal of Marketing*, 55(1), pp. 52-69.

Frei R., Zhang D., Bayer S., Gerding E., Wills G., & Speights D. (2023). *What factors drive product returns in multichannel retail?* SSRN working paper, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4410055

Frei, R., Jack, L., & Brown, S. (2020). Product returns: a growing problem for business, society and environment. *International Journal of Operations & Production Management*, 40(10), 1613-1621.

Goretzko, D., Pham, T.T.H., & Bühner, M. (2021). "Exploratory factor analysis: Current use, methodological developments and recommendations for good practice". *Current Psychology*, 40, pp.3510-3521.

Hair JF, Tatham RL, Anderson RE., & Black W (1998). *Multivariate data analysis*, 5th edition. Prentice-Hall, London.

Harris, L. C. (2008). Fraudulent Return Proclivity: An Empirical Analysis. *Journal of Retailing*, 84(4), 461-476.

Harris, L. C. (2010). Fraudulent consumer returns: exploiting retailers' return policies. *European Journal of Marketing*, *44*(6), 730-747.

Heiman, A., McWilliams, B., & Zilberman, D. (2001). Demonstrations and money-back guarantees: Market mechanisms to reduce uncertainty. *Journal of Business Research*, 54(1), 71-84.

Higuchi, A., & Maehara, R. (2021). "A factor-cluster analysis profile of consumers". *Journal of Business Research*, 123, pp.70-78.

Hjort, K., Hellström, D., Karlsson, S., & Oghazi, P. (2019). Typology of practices for managing consumer returns in internet retailing. *International Journal of Physical Distribution & Logistics Management*, 49(7), 767-790.

Howard, M.C., (2023). "A systematic literature review of exploratory factor analyses in management". Journal of Business Research, 164.

Homer, E. M. (2020). Testing the fraud triangle: a systematic review. *Journal of Financial Crime*, *27*(1), 172-187.

Hübner A, Wollenburg J, Holzapfel A (2016) Retail logistics in the transition from multi-channel to omni-channel. *International Journal of Physical Distribution & Logistics Management*, 46(6/7):562-583.

Ishfaq, R., Raja, U., & Rao, S. (2016). Seller-induced scarcity and price-leadership: Impact on product returns in the internet retail supply chain. *The International Journal of Logistics Management*, 27(2), 552-569.

Jack L, Frei R., & Krzyzaniak SA (2019). *Buy Online, Return to Store; The Challenges and Opportunities of Product Returns in a Multichannel Environment*. Research commissioned by the ECR Shrink Group. Available at: https://www.ecrloss.com/research/buy-online-return-in-store

Janakiraman, N., Syrdal, H. A., & Freling, R. (2016). The effect of return policy leniency on consumer purchase and return decisions: A meta-analytic review. *Journal of Retailing*, 92(2), 226-235.

Johnson, K. K., & Rhee, J. (2008) An Investigation of Consumer Traits and their Relationship to Merchandise Borrowing with Undergraduates. *Journal of Family & Consumer Sciences Education*, *26*(1).

Jolson, M. A. (1974). Consumers as offenders. Journal of Business Research, 2(1), 89-98.

Jones, A. L., Miller, J. W., Whipple, J. M., Griffis, S. E., & Voorhees, C. M. (2024). The effect of perceptions of justice in returns on satisfaction and attitudes toward the retailer. *International Journal of Physical Distribution & Logistics Management*, *54*(1), 40-60.

Kerlinger, F.N. (1986). *Foundations of Behavioral Research*, 3rd edition. Holt, Rinehart and Winston, New York, NY.

Kang, M., & Johnson, K. (2009). Identifying characteristics of consumers who frequently return apparel. Journal of Fashion Marketing and Management, 13(1), 37-48.

King, T., & Dennis, C. (2003). Interviews of deshopping behaviour: an analysis of theory of planned behaviour. *International Journal of Retail & Distribution Management*, *31*(3), 153-163.

King, T., & 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), 282-296.

King, T., Dennis, C., & Wright, L. T. (2008). Myopia, customer returns and the theory of planned behaviour. *Journal of Marketing Management*, *24*(1-2), 185-203.

Lee, CF., Lee, J.C., & Lee, A.C. (2013). Nonparametric Statistics. In: Statistics for Business and Financial Economics. Springer, New York, NY.

Levi, M., & Smith, R.G. (2021), *Fraud and its relationship to pandemics and economic crises: from Spanish flu to COVID-19*, Australian Institute of Criminology. Available at: https://apo.org.au/node/312080 (Accessed 12 Sept 2023)

National Retail Federation. (2020). 2020 Consumer Returns in the Retail Industry. https://cdn.nrf.com/sites/default/files/2023-01/AR3020-2020%20Customer%20Returns%20in%20the%20Retail%20Industry_1.7.21.pdf

National Retail Federation. (2023). 2023 Consumer Returns in the Retail Industry.

Nunnally, J.C. (1978). *Psychometric Theory*, 2nd ed.. McGraw-Hill, New York.

Moynihan, Q., & Aguiar, A.R., 2019, August 01. A 22-Year-Old Is Accused of Scamming Amazon Out of Nearly $370,000 by Sending Back Boxes Weighted with Dirt Instead of the Returned Product. Retrieved from. https://www.businessinsider.com/22-year-old-mud-filled-boxes-scam-amazon-370000-2019-8?r=US&IR=T (Accessed 12 Sept 2023)

ONS. (2022). Analysis of Population Estimates Tool. Available at: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates. (Accessed 21 December 2023).

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology*, 45(4), 867-872.

Peacock, C. (2023). UK Grocery sector reports a 33% increase in Unknown Loss (Shrink). Available at: https://www.ecrloss.com/blog/uk-grocery-retailers-report-a33-increase-in-shrink (Accessed 12 September 2023).

Peer, E., Brandimarte, L., Samat, S., & Acquisti, A. (2017). Beyond the Turk: Alternative platforms for crowdsourcing behavioral research. *Journal of Experimental Social Psychology*, *70*, 153-163.

Peer, E., Rothschild, D., Gordon, A., Evernden, Z., & Damer, E. (2022). Data quality of platforms and panels for online behavioral research. *Behavior Research Methods*, 54(4), 1643–1662.

Pei, Z., & Paswan, A. (2018). Consumers' legitimate and opportunistic product return behaviors in online shopping. *Journal of Electronic Commerce Research*, 19(4), 301-319.

Pellathy, D. A., In, J., Mollenkopf, D. A., & Stank, T. P. (2018). Middle-range theorizing on logistics customer service. *International Journal of Physical Distribution & Logistics Management*, 48(1), 2-18.

Petersen, J. A., & Kumar, V. (2009). Are product returns a necessary evil? Antecedents and consequences. *Journal of Marketing*, *73*(3), 35-51.

Phau, I., Akintimehin, O., Shen, B., & Cheah, I. (2022). “Buy, wear, return, repeat”: Investigating Chinese consumers' attitude and intentions to engage in wardrobing. *Strategic Change*, *31*(3), 345-356.

Piron, F., & Young, M. (2000). Retail borrowing: insights and implications on returning used merchandise. *International Journal of Retail & Distribution Management*, *28*(1), 27-36.

Punj, G., & Stewart, D.W. (1983). "Cluster analysis in marketing research: Review and suggestions for application". *Journal of Marketing Research*, 20(2), pp.134-148.

Returnalyze (2023). https://www.returnalyze.com/blog/the-scary-truth-about-returns-abuse (Accessed 12 August 2024)

Robertson, T. S., Hamilton, R., & Jap, S. D. (2020). Many (un) happy returns? The changing nature of retail product returns and future research directions. *Journal of Retailing*, 96(2), 172.

Rokonuzzaman, M., Iyer, P., & Harun, A. (2021). Return policy, No joke: An investigation into the impact of a retailer's return policy on consumers' decision making. *Journal of Retailing and Consumer Services*, 59, 102346.

Röllecke, F. J., Huchzermeier, A., & Schröder, D. (2018). Returning customers: The hidden strategic opportunity of returns management. *California Management Review*, 60(2), 176-203.

Rosenbaum, M. S., Kuntze, R., & Wooldridge, B. R. (2011). Understanding unethical retail disposition practice and restraint from the consumer perspective. Psychology & Marketing, 28(1), 29-52.

Rosenthal, S. (2019). How Can Retailers Address the Growing Problem of Wardrobing. *risnews.com*. https://risnews.com/how-can-retailers-address-growing-problem-wardrobing (Accessed 2 Oct 2023)

Rozenkowska, K. (2023). Theory of planned behavior in consumer behavior research: A systematic literature review. *International Journal of Consumer Studies*, 47(6), 2670-2700.

Russo, I., Pellathy, D., & Omar, A. (2021). Managing outsourced reverse supply chain operations: Middle-range theory development. *Journal of Supply Chain Management*, 57(4), 63-85.

Russo, I., Masorgo, N., & Gligor, D. M. (2022). Examining the impact of service recovery resilience in the context of product replacement: the roles of perceived procedural and interactional justice. *International Journal of Physical Distribution & Logistics Management*, *52*(8), 638-672.

Saunders, J.A. (1980). "Cluster analysis for market segmentation". *European Journal of Marketing*, 14(7), pp.422-435.

Schuchter, A., & Levi, M. (2016). The fraud triangle revisited. Security Journal, 29, 107-121.

Service Central (2023). The Perfect Retailer's guide to prevent return frauds at a large scale. https://www.servicecentral.com/news/the-perfect-retailers-guide-to-prevent-return-frauds-at-a-large-scale/ (Accessed 12 August 2024)

Shamiss, S. (2024). Five Ways That Returns Fraud Is Costing Retailers Money. Supply Chain Brain, online: https://www.supplychainbrain.com/blogs/1-think-tank/post/38995-five-ways-that-return-fraud-is-costing-retailers-money (Accessed 12 August 2024)

Shang, G., Ferguson, M. E., & Galbreth, M. R. (2019). Where should I focus my return reduction efforts? Empirical guidance for retailers. *Decision Sciences*, *50*(4), 877-909.

Shang, G., Ghosh, B. P., & Galbreth, M. R. (2017). Optimal retail return policies with wardrobing. *Production and Operations Management*, *26*(7), 1315-1332.

Speights, D., & Hilinski, M. (2005). Return fraud and abuse: How to protect profits. *Retailing Issues Letter*, *17*(1), 1-6.

Stank, T.P., Pellathy, D.A., In, J., Mollenkopf, D.A. and Bell, J.E. (2017). New frontiers in logistics research: theorizing at the middle range. *Journal of Business Logistics*, 38(1), 6-17.

Swinyard, W.R., & Smith, S.M. (2003). Why people (don't) shop online: A lifestyle study of the internet consumer. *Psychology & Marketing*, 20: 567-597.

Škapa, R. (2013). Application of the theory of planned behavior to fraudulent returning. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 60(7), 379-386.

The Crown Prosecution Service (2006). *Fraud Act 2006*. Available at: https://www.cps.gov.uk/legal-guidance/fraud-act-2006 (accessed 9th Jan 2022).

Wang, Y., Wiegerinck, V., Krikke, H., & Zhang, H. (2013). Understanding the purchase intention towards remanufactured product in closed-loop supply chains: An empirical study in China. International Journal of Physical Distribution and Logistics Management, 43(10), 866–888.

Young, S (2019). Asos to blacklist 'serial returners' who demand refunds after wearing clothes bought online. Available at: https://www.independent.co.uk/life-style/returning-clothes-asos-harrods-online-shopping-wear-return-pictures-social-media-instagram-a8750116.html (accessed 2nd September 2022).

Zhang, D., Bayer, S., Wills, G. B., Frei, G., Gerding, E. H., & Senyo, P. K. (2022, April). Using Big Data Analytics to Combat Retail Fraud. In Proceedings of the 4th International Conference on Finance, Economics, Management and IT Business (pp. 85-92). (doi)

Zhang, D., Frei, R., Senyo, P. K., Bayer, S., Gerding, E., Wills, G., & Beck, A. (2023). Understanding fraudulent returns and mitigation strategies in multichannel retailing. Journal of Retailing and Consumer Services, 70, 103145.

Appendices

Appendix 1: Bivariate Pearson correlation of policies' evaluations across types of fraudulent behaviour

Wardrobing	Shorter return period	Customer desk returns	Return labels request	Return with tags attached	Returns shipping fee	Exchange/ refund onto a gift card	Mandatory account registration	Serial returners ban
Shorter return period	1	0.289**	0.316**	0.124**	0.212**	0.160**	0.190**	0.054
Customer desk returns	0.289**	1	0.352**	0.249**	0.239**	0.135**	0.288**	0.173**
Return labels request	0.316**	0.352**	1	0.169**	0.326**	0.134**	0.368**	0.121**
Return with tags attached	0.124**	0.249**	0.169**	1	0.100*	0.045	0.210**	0.218**
Returns shipping fee	0.212**	0.239**	0.326**	0.100*	1	0.444**	0.269**	0.315**
Exchange/refund onto a gift card	0.160**	0.135**	0.134**	0.045	0.444**	1	0.262**	0.290**
Mandatory account registration	0.190**	0.288**	0.368**	0.210**	0.269**	0.262**	1	0.308**
Serial returners ban	0.054	0.173**	0.121**	0.218**	0.315**	0.290**	0.308**	1

Damaged item returns	Shorter return period	Customer desk returns	Return labels request	Return with tags attached	Returns shipping fee	Exchange/ refund onto a gift card	Mandatory account registration	Serial returners ban
Shorter return period	1	0.382**	0.420**	0.324**	0.214**	0.219**	0.231**	0.134**
Customer desk returns	0.382**	1	0.465**	0.280**	0.230**	0.252**	0.322**	0.198**
Return labels request	0.420**	0.465**	1	0.316**	0.493**	0.325**	0.534**	0.242**
Return with tags attached	0.324**	0.280**	0.316**	1	0.301**	0.258**	0.296**	0.200**
Returns shipping fee	0.214**	0.230**	0.493**	0.301**	1	0.566**	0.426**	0.355**
Exchange/refund onto a gift card	0.219**	0.252**	0.325**	0.258**	0.566**	1	0.376**	0.397**
Mandatory account registration	0.231**	0.322**	0.534**	0.296**	0.426**	0.376**	1	0.442**
Serial returners ban	0.134**	0.198**	0.242**	0.200**	0.355**	0.397**	0.442**	1

Damaged item returns	Shorter return period	Customer desk returns	Return labels request	Return with tags attached	Returns shipping fee	Exchange/ refund onto a gift card	Mandatory account registration	Serial returners ban
Shorter return period	1	0.382**	0.420**	0.324**	0.214**	0.219**	0.231**	0.134**
Customer desk returns	0.382**	1	0.465**	0.280**	0.230**	0.252**	0.322**	0.198**
Return labels request	0.420**	0.465**	1	0.316**	0.493**	0.325**	0.534**	0.242**
Return with tags attached	0.324**	0.280**	0.316**	1	0.301**	0.258**	0.296**	0.200**
Returns shipping fee	0.214**	0.230**	0.493**	0.301**	1	0.566**	0.426**	0.355**
Exchange/refund onto a gift card	0.219**	0.252**	0.325**	0.258**	0.566**	1	0.376**	0.397**
Mandatory account registration	0.231**	0.322**	0.534**	0.296**	0.426**	0.376**	1	0.442**

Serial returners ban	0.134**	0.198**	0.242**	0.200**	0.355**	0.397**	0.442**	1

Price arbitrage	**Shorter return period**	**Return with tags attached**	**Purchase receipt requirement**	**Return labels request**	**Returns shipping fee**	**Exchange/ refund onto a gift card**	**Mandatory account registration**	**Serial returners ban**
Shorter return period	1	0.127**	0.229**	0.418**	0.302**	0.290**	0.304**	0.135**
Return with tags attached	0.127**	1	0.461**	0.265**	0.238**	0.248**	0.183**	0.355**
Purchase receipt requirement	0.229**	0.461**	1	0.485**	0.278**	0.290**	0.381**	0.341**
Return labels request	0.418**	0.265**	0.485**	1	0.623**	0.365**	0.601**	0.332**
Returns shipping fee	0.302**	0.238**	0.278**	0.623**	1	0.462**	0.487**	0.317**
Exchange/refund onto a gift card	0.290**	0.248**	0.290**	0.365**	0.462**	1	0.347**	0.283**
Mandatory account registration	0.304**	0.183**	0.381**	0.601**	0.487**	0.347**	1	0.463**
	0.135**	0.355**	0.341**	0.332**	0.317**	0.283**	0.463**	1

Stolen item returns	**CCTV**	**Customer desk returns**	**Return with tags attached**	**Exchange/refund onto a gift card**	**Mandatory account registration**
CCTV	1	0.297**	0.215**	0.123**	0.320**
Customer desk returns	0.297**	1	0.541**	0.427**	0.479**
Return with tags attached	0.215**	0.541**	1	0.489**	0.373**
Exchange/refund onto a gift card	0.123**	0.427**	0.489**	1	0.335**
Mandatory account registration	0.320**	0.479**	0.373**	0.335**	1

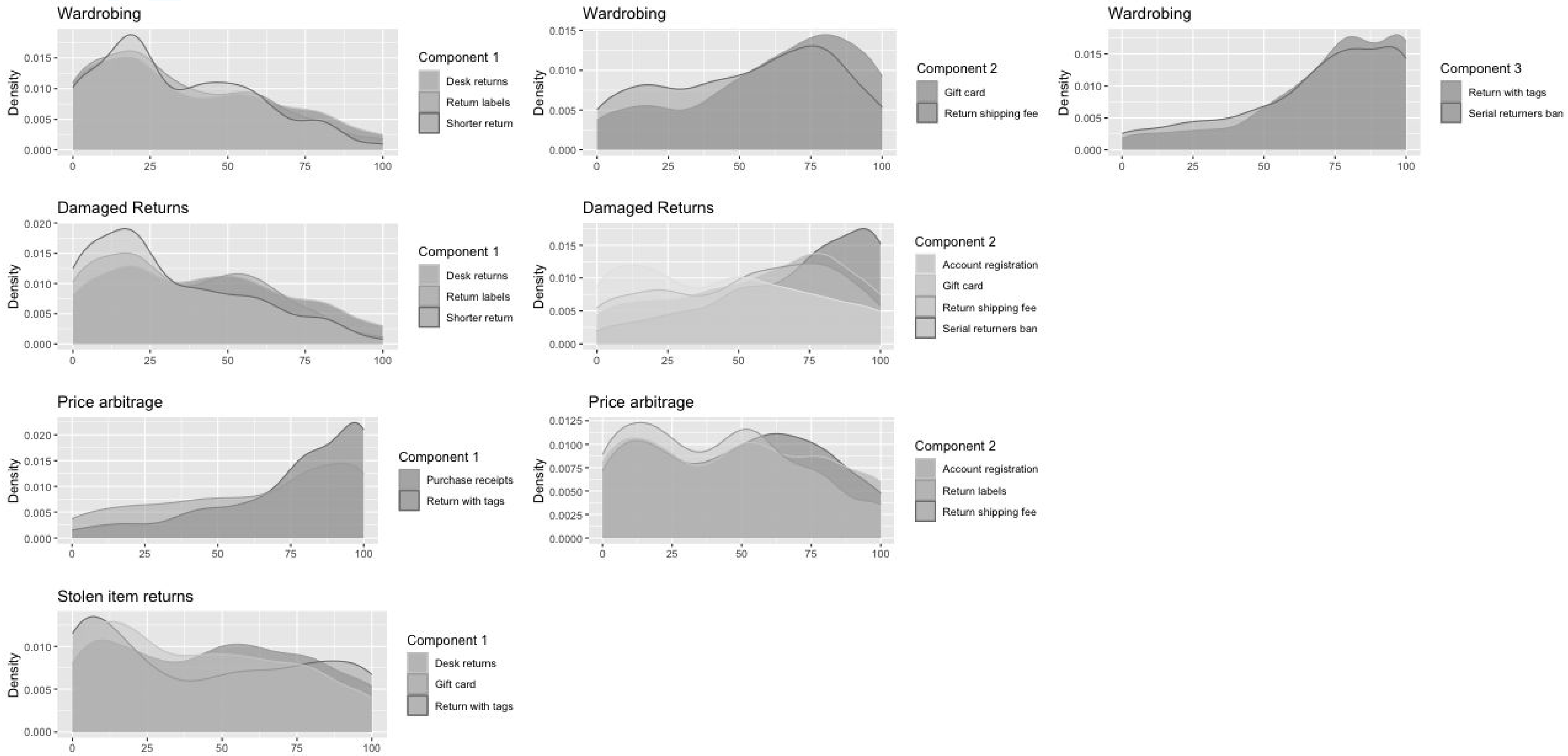
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

Appendix 2: Mean evaluation scores of policy effectiveness across different returns fraud types

Policies	**Wardrobing**	**Damaged returns**	**Price arbitrage**	**Stolen item returns**
CCTV	-	-	-	64 (26)
Purchase receipt requirement	-	-	63 (31)	-
Shorter return period	34 (25)	31 (25)	23 (24)	-
Customer desk returns	37 (28)	42 (28)	-	42 (30)
Return labels request	34 (26)	36 (26)	42 (29)	-
Return with tags attached	73 (26)	69 (29)	75 (26)	44 (35)
Returns shipping fee	53 (29)	54 (30)	48 (30)	-
Exchange/refund onto a gift card	62 (29)	58 (29)	54 (30)	47 (31)
Mandatory account registration	43 (30)	44 (31)	47 (32)	61 (29)
Serial returners ban	69 (28)	69 (27)	73 (27)	-

Mean scores provided, 0-100 scale (Standard deviation in brackets)

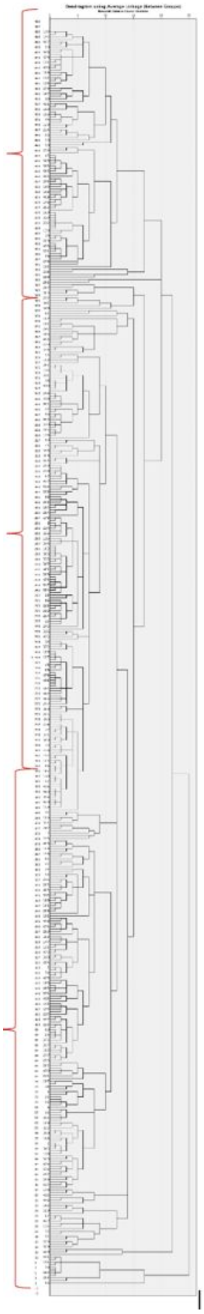
Appendix 3: Kernel density estimate for effectiveness across components (columns) and fraud types (rows)



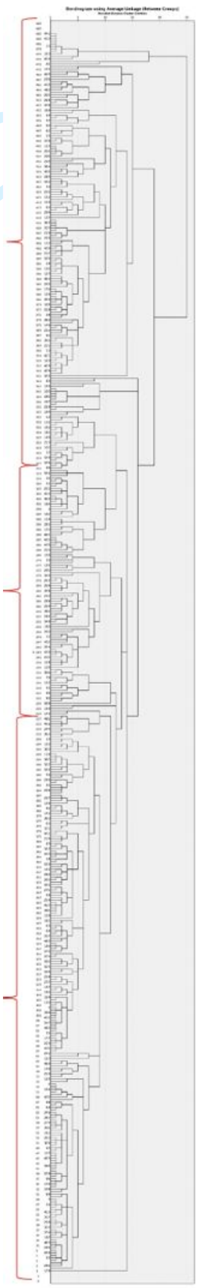
** See* Table F *for details about each component.*

Appendix 4: Hierarchical cluster dendrogram analysis for each type of fraudulent behaviour

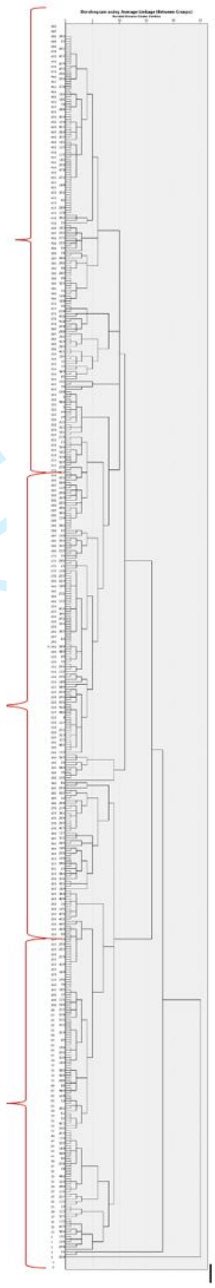
1. Wardrobing



2. Damaged Fraud



3. Price Arbitrage



4. Stolen Item Return