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Reduction of the product return rate in e-commerce : the use of nudges

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1. Introduction

In a world where consumers are increasingly turning to e-commerce, new issues are emerging. E-commerce, or online retailing, is the term used to describe the purchasing and selling of goods and services via the internet (Pagano et al., 2024). Buying from a distance offers major advantages for both consumer and retailer, such as simplicity, accessibility and speed, but consumers have to base their purchasing decisions exclusively on images and information provided by the retailer. To compensate for this disadvantage, retailers usually offer to the consumers the option of returning products that are unsuitable, with a total refund at no extra cost (Janakiraman et al., 2016).

But those returns come at a price: In 2022, the predicted $1.29 trillion in U.S. online retail sales included $212 billion in returned goods, or 16.4% of total sales (Amorim et al., 2023). According to Navar (2023), a post-purchase platform, businesses pay in average $33 for each return taking into consideration labour costs, missed sales windows, postage, packaging, and value reduction. On the other hand, product returns have a significant detrimental impact on the environment (Calma, 2019). Through their carbon dioxide emissions and additional garbage, product returns add to environmental pollution and contribute to climate change (Tian & Sarkis, 2022). Over five billion pounds of returned goods and packaging wind up in landfills each year in the United States and, due to the transportation of returns produce over 15 million additional metric tons of carbon dioxide (Calma, 2019).

As a result, companies are becoming increasingly wary of this free returns policy and are starting to implement "keep it" policies by imposing return charges on consumers (Baertlein & McLymore, 2023). But we will see later that this solution is not necessarily satisfactory for retailers. The challenge of product returns from e-commerce represents a huge challenge for companies from a financial point of view, and for society in general in terms of greenhouse gas emissions. This is why trying to reduce the propensity of consumers to reduce their returns is so important. The aim of this thesis is to find a way of reducing the return rate of e-retailers without altering the return policy leniency. To do this, we will extend the literature on green nudges that reduce the rate of return, which are currently largely understudied, by testing the effectiveness of 2 different types of nudges and by testing a moderating variable and a mediating variable to understand how they work.

2. Literature review

2.1. Product return

2.1.1 Definition

The Cambridge dictionary describes product return as “a situation in which a buyer does not want a product and returns it to the company to get their money back”. Product returns (PR) are a necessary but expensive procedure for a company, particularly in e-commerce. Practitioners and researchers alike have focused a considerable deal of effort on how to handle the conundrums (Duong, 2022). To put this concept into a broader context, Chircu & Mahajan (2006) define the retail transaction as a series of processes that include entering the store, looking around, deciding what to buy, placing an order, paying for it, having it filled, and receiving after-sale support. Each of these stages comes with a price, a time cost (waiting time, delivery time), a monetary cost (taxes, credit charges, etc.), or a psychological cost (convenience, aggravation, perceived ease of use, annoyance, etc.).

At each stage of the process, managerial choices about the return policy and several other operational factors may have an impact on how customers behave. Pre-purchase, post-purchase, and post-return decisions and activities must be managed separately from the retailer's perspective (Abdulla et al., 2019). Before a customer makes a purchase, the retailer must create a return policy, offer information, establish price, and carry out all other operational planning tasks required for successful retail execution. Naturally, the performance of retailers also persists in the context of post-sale services, such as customer relationship management, warranty assistance, and physical processing of returned goods. Four broad and interconnected study domains—return policy (RP), consumer behaviour (CB), planning and execution (PE), and return management (RM)—emerge when viewed collectively from the customer and retailer viewpoints. (Abdulla et al., 2019) These four domains work together to create a conceptual framework that can categorize research contributions in the consumer returns area in a meaningful way.

- Return policies are characterized by their leniency, which relates to how simple and convenient it is for customers to make returns.
- The domain of return management covers the efficient and effective gathering, processing, and disposition of returns. Return policy decisions are likely to be

influenced by a retailer's return management infrastructure and practices, and vice versa. (Abdulla et al., 2019)

- The consumer behaviour domain specifically takes the consumer's decision-making process into account when it comes to sales and refunds.
- The planning and execution domain captures how returns affect supply chain management and forward logistics. (Abdulla et al., 2019)

In this thesis, we will only focus on the return policies and the consumer behaviour because it is complicated to analyse all 4 aspects of the literature on product returns, which is so extensive. As the aim of this dissertation is to find a way of persuading consumers not to return products, only the two areas mentioned seem to be concerned.

2.1.2. Return policies

According to Janakiraman et al. (2016), five factors can be used to categorize return policies as lenient or restrictive:

1. Time leniency. Retailers frequently include deadlines in their return policies (such as a 30-day period). Return policies that give customers more time to return goods are thought to be more lenient.
2. Monetary leniency. While tight return policies only allow for a percentage of the purchase price to be refunded—typically by imposing a non-refundable "shipping and handling fee" or a "restocking fee"—lenient policies allow for a reimbursement of the whole amount paid for the product. Financially-neutral policies are thought to be more permissive.
3. Effort leniency. The amount of work that customers must put in to complete returns varies, and some retailers make it more difficult for customers to return goods (by, for example, demanding that the original product packing, receipt, or tags be kept). Return policies that are less demanding on the customer are regarded as being more forgiving.
4. Scope leniency. Retailers restrict what they deem to be "return-worthy." For instance, goods bought during a sale might not be returnable. More items that qualify as "return-worthy" returns are covered by more permissive return policies.
5. Exchange leniency. While some companies just give cash back, others will replace the returned item for store credit or another product. Refunds in cash are permitted under more permissive return conditions.

In their paper Janakiraman et al. (2016) tried to see what effect these 5 factors had on consumers' purchase attention and on the return attention of these same products. According to them, companies need to create more complex policies that vary along multiple dimensions and that take account of the objective. For example, if they want to increase turnover, they need to focus on monetary leniency or effort leniency. On the other hand, if the objective is simply to reduce returns, then time leniency, scope leniency and exchange leniency are the ones to focus on.

2.1.3. Determinants of product returns

The choice between these different returns policies are decisions taken by the company, but it does not explain the consumer's choice to return a product when they have the opportunity to do so. Researchers put forward different reasons to explain this choice, depending on their research angle. Various studies on the subject have adopted different ways of categorizing these reasons.

Driving forces

In Von Zahn et al. (2022), researchers have distinguished between legitimate, opportunistic, and fraudulent product returns as the driving forces behind return decisions (Pei and Paswan 2018). Fraudulent returns do not adhere to the retailer's legal guidelines, they consist of returning goods that have been damaged by consumers or that have been stolen (Zhang et al., 2023). The number of fraudulent returns has risen sharply in recent years, and it is very difficult to combat them (Baertlein & McLymore, 2023). Opportunistic returns and legitimate returns both adhere to the return policies of the shops, although they differ from one another significantly. In the legitimate returns, customers had a sincere desire to keep the items when they initially ordered the rightfully returned goods. Opportunistic returns, on the other hand, constitute 4% to 6% of returns in 2015 and involve ordered goods with a pre-made intention to return, such as when clients bracket and order the same item in many sizes even if they know they will only keep one of them (Altug et al., 2021). Legitimate returns make up most returns. As proof, clothing has the highest average return rate of any online item (26%), closely followed by other accessories (13%), bags & accessories (19%), and shoes (18%). The sizing may run small or large, and online buyers may not always be able to determine whether the color and style listed in the product descriptions really represent the actual item (Trapnell, 2023).

The original motivation for the purchase may also have an impact on the propensity to make a return. When purchases are motivated by hedonism, unplanned purchases (as opposed to planned purchases) result in higher probability of return. On the other hand, when purchases are motivated by utilitarian considerations, planned and unplanned purchases produce similar levels of concern and probability of return. Nevertheless, the returns policy moderates this two-way interaction: when a lenient return policy is proposed by the retailer and highlighted, the purchase plan and purchase motivations no longer interact to influence purchase intentions (Seo et al., 2015).

Taxonomy of return reasons

In their qualitative study of online return behaviour of young consumers, Das & Kunja (2024) identified 7 reasons influencing the decision of returning a product bought online by young consumers. These reasons are categorized into two distinct groups depending on if they are controlled by the selling company or by the customer. The company-centric reasons are; unsuitable product, compromised delivery, manipulated information and deceptive advertisement. The consumer-centric reasons are; the buyer’s spontaneity, the buyer’s regret and wardrobing. The latter can be described as form of fraud in which an item is purchased and then returned to the shop after being used in order to obtain a refund and refers to the fraudulent return in Von Zahn et al. (2022).

Other determinants

Customer characteristics also influence the number of product returns. Liberman & Trope (1998) found that, in various consumer choice situations, people rated a service's feasible attributes—such as delivery method, costs, etc.—as extremely relevant elements, showing a concrete thinking. With a larger time span, people, however, have a propensity to concentrate more on abstract desirable traits. This suggests that customers who have high time leniency may concentrate more on product fit and experience benefits, which could lead to a different post-purchase outcome than those who have low time leniency, who would concentrate more on factors like product price and return effort.

This dimension of time is also underlined by Wood who gives the endowment effect as another reason for product return. The endowment effect, where one appreciates what they currently own more than what they do not yet own, is a fascinating phenomenon explored by prospect theory. A longer return window should improve a customer's valuation of a product and lead to a decreased chance of returns, according to the endowment effect in the context of time leniency (Wood, 2001).

From another perspective, in the specific case of e-commerce live-broadcasts, Huang (2023) has established a causal link between the quality of the return service (long return time, low effort and high refund guarantee) and the e-commerce return rate. This empirically proven link can be summarized as follows: “E-commerce return and exchange service improves e-commerce purchase rate, e-commerce purchase rate increases e-commerce return rate, and e-commerce return and exchange service improves e-commerce return rate” (Huang, 2023).

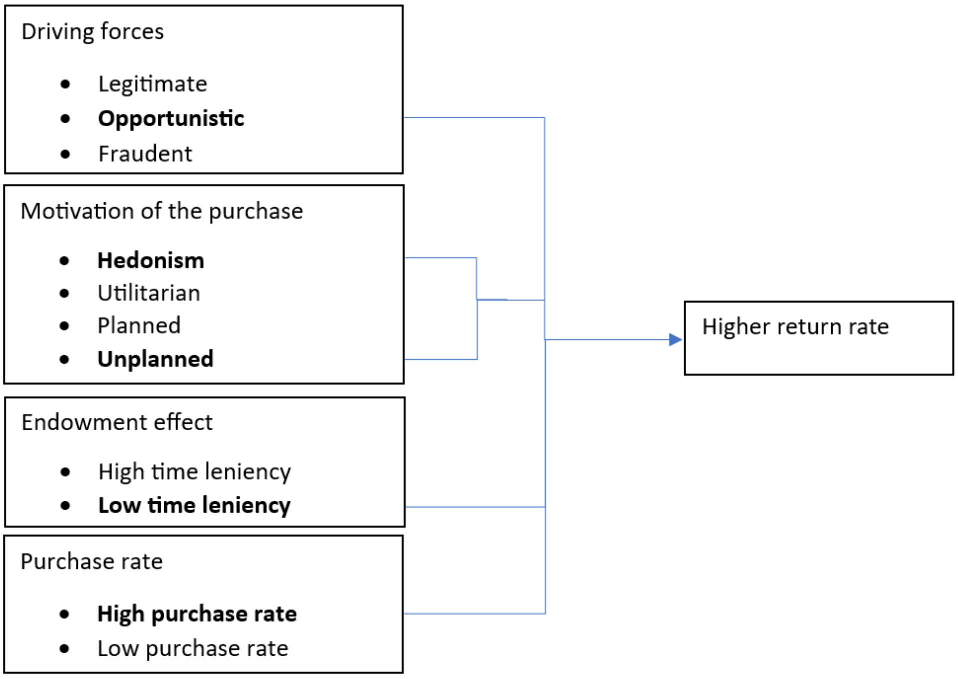

Figure 1: Reason of high return rate

2.1.4. Product return reduction

From the exclusive perspective of discouraging product returns, Walsh & Möhring (2017) propose 3 main categories of tools (2 of which are linked to the leniency of the return policy): monetary, procedural, and customer-based.

- Monetary mechanisms, like discounts on future purchases, are not necessarily a good approach to lower the return rate because beside encouraging the purchasing act by signalling the quality of the product, it makes people buy more because of a low perceive risk according to Walsh & Möhring (2017). As people are more likely to buy without considering the consequences of the purchase, they are more likely to regret their choice and to return the product. This category of tool corresponds to the monetary leniency factor explained above.
- Procedural instruments focus on the post-purchase phases and persuade customers to keep a product by improving the ordering and shipping processes. For example, attractive packaging and extras can make customers having positive emotion, which in turn lowers the likelihood that they will actually return items. Alternatively, by limiting the number of possible return channels or requiring customers to "print yourself" return tickets, retailers can also make the return process less convenient. The time leniency and effort leniency can reflect this particular tool.
- Customer-based tools, on the other hand, function both before and during the purchase phase. When there is a significant discrepancy between customer expectations and actual product attributes, customers are more likely to return things. As a result, many customer-based instruments currently in use operate under the assumption that knowing more about a product's attributes will help people have more accurate expectations of it, which will lower legitimate and profitable returns related to expectancy-reality dissonances. Virtual try-on sessions, alternate product images, customer feedback, and online consultation assistance or demonstrations are frequently suggested consumer-based tools . In their paper, Walsh & Möhring (2017) find that using product review can lower the return rate from 5,7% to 3,8%. This

proposed tool does not really involve return policy per se. Here it is more a question of the customer's satisfaction on receiving the product and not really the way in which they are entitled to return it.

For the moment, the majority of studies aimed at reducing the number of returns produced focus on the leniency of the return policy (Shang et al., 2018). Whether or not a generous product return policy is justified is a subject that divides researchers. Some believe that an overly generous policy increases the quantity of returns more than it increases sales, thereby reducing profit. Others, on the other hand, believe that sales increase more than returns, thus boosting profits. As the various scientific papers do not agree on this point, it is difficult to give a clear answer.

According to the analysis of Janakiraman et al. (2016), return policies with greater tolerance towards money and/or effort are likely to boost customer purchases, which in turn is likely to stimulate demand. Retailers should pay more attention to other factors, such as return policy deadlines, exchange leniency, and/or scope leniency, when reducing returns is the top priority because those are the most influent factors in terms of return proclivity.This implies that lax return policies help retailers generally, because the raise of profits made by the increase of the sales is more important than the increase of the product returns.
Another statement of Janakiraman et al. (2016) is that rather than enacting a uniform return policy for every item in the store, distinct return policies should be developed for each category of products sold there, as evidenced by the finding that lenient return policies significantly increase purchases of durable products compared to non-durable products. For example, the time leniency lever could be investigated in a situation with several product categories, where the goal is to create an optimization framework to choose the best return policy portfolio by giving different product categories discretized return time windows. By demonstrating category-level variability in return timing, Shang et al. (2018) also examine the possible advantages of a portfolio of category-based return policies with different time leniency. Retailers might be better benefited by developing more complex return policies that vary along numerous dimensions as opposed to simple return policies that vary along only one or two dimensions, given the various influences of the leniency variables.

Conversely, Altug et al. (2016) try to show that a full-refund equilibrium is optimal by changing a number of important modelling assumptions. According to them, lenient return policies are not the best option and for instance, partial refund policies are recommended in many studies since full refunds are too generous and can expose a retailer to expensive opportunistic behaviour. Partial reimbursements are preferable, according to Altug et al. (2016), even when opportunism is not taken into account. However, in reality, the majority of retailers give full refunds for at least a while after a customer makes a purchase. As stated by Altug et al. (2016), the potential negative consequences of adopting a partial refund policy instead of a long-standing full refund policy could be one reason why big retailers continue to maintain full return policies. In fact, a lot of merchants appear to be aware that having overly lax return policies hurts their bottom line yet nonetheless include them as a key component of their value proposition. In practice, retailers may choose for a less-than-ideal policy due to strategic or competitive factors. According to empirical study, customers have a very negative perception of partial refund policies, which may reduce their good behavioural intentions and outcomes (Pei et al., 2014). Furthermore, there is a lot of anecdotal evidence to support a shift in consumers' attitudes away from merchants who impose restrictions on formerly tolerant practices or demand restocking fees.

Despite this, more and more e-commerce players are adopting a "returnless" or "keep it" policy for products whose value does not exceed the cost of a return for the company. According to a survey of 500 retail executives, the number of companies with such a policy has risen from 26% in 2022 to 59% in 2023. (Baertlein & McLymore, 2023)

In addition to the return policy studies explained above (Janakiraman et al., 2016; Altug et al., 2016; Shang et al., 2018), table 1 summarize a few studies with the same scope. While various return policies have already been studied extensively in order to reduce returns, we can see that the results are not consistent with each other. Some conclude that a lenient policy is profitable for the retailer, while others conclude that a restrictive policy is profitable for the retailer. A general truth cannot be established because the profitability of return policy choices depends too much on the specific context of each company (products, costs, reputation, etc.) (Abdulla et al., 2019).

Therefore, we could imagine that there are other solutions not based on the leniency of the return policy that could achieve the same objective. To solve this problem with more subtle instruments, we can call on a recently created tool called nudge that enables us to influence an influencer's decisions without significantly changing the product and the associated offer.

Table 1: Summary of papers studying return policy leniency

Authors	Dimension	Studies	Findings
Janakiraman & Ordónez (2012)	Time and effort leniency	Examine the effect of deadlines on product return considering the effort.	Extended expiration dates enhance the endowment effect of products and cause consumers to put off or postpone return choices. Thus, longer deadlines may lead to lower return rates because the cost of the item feels less severe to the consumer, over time, and is therefore less of a motivation to return an item.
Petersen & Kumar (2010)	Scope leniency	Examine the link between product returns, return leniency and profits.	There is a stronger rise in purchases as a result of lenient return policies than in terms of return rates. This implies that return policies help retailers generally, at least in terms of promoting product purchases.
Bower & Maxham (2012)	Monetary leniency	Examine if a return policy where the customer pays to return the product if he is at fault can be benefic.	Retailers need to have a free returns policy, because when returns have to be paid for, customers stop buying from them.
Shulman, Coughlan, & Savaskan (2010)	Monetary leniency	Examine the effect of restocking penalties	Lower return penalty increases the expected utility of initially making a purchase
Kim & Wansink (2012)	Time, Monetary, effort, scope and exchange leniency	Examine how customers' post-purchase product evaluations are impacted by the suggestions and return policies.	When there is pre-purchase recommendation, the post-purchase evaluation is more favourable with lenient return policy but when there is no recommendations the evaluation is better with restricted return policies.
Lantz & Hjort (2013)	Monetary leniency	Explore the influence of free delivery and free returns on the purchasing and return behaviour of real e-customers	A lenient delivery policy is associated with increased order frequency, decreased average value of purchased items, increased probability of return, and increased average value of returned items

2.2. Nudges

Another approach that can be useful in reducing product returns is the use of nudges. By empowering individuals to make better decisions, nudge interventions can lower market failure and boost resource efficiency as a customer-based tool. Online retailers use a range of influencing strategies to try to increase their revenues, but these strategies are also used to improve social welfare (Ghose, 2023).

2.2.1 Definition

Behavioural economist Richard Thaler and the legal expert Cass Sunstein invented the concept of “nudge” in 2008. A nudge can be described as a choice architecture design element that aims to influence people's behaviour in a predictable way without significantly altering their material incentives, restricting their option set, or using coercion (Mirsch et al. 2017, Thaler & Sunstein 2008). Setting a default option, drawing attention to certain options, drawing attention to social norms, slightly altering how easy it is to choose certain options, creating a psychological anchor, and giving people specific information are examples of common nudges (Weinmann et al., 2016). The use of nudging can help achieve a variety of goals and is relevant in a wide range of situations.

Choice circumstances have been included into online contexts for everything from e-government to e-commerce interactions. While many nudging tactics (such as the use of framing or appealing to norms) are tied to content or terminology, other nudging strategies can be used simply changing the way user interfaces are designed. Choice architects, who design the decision environment, are thereby attempting to influence or direct people's behaviour through digital nudges. Weinman et al. define digital nudging as “ the use of user interface design elements to guide people’s choices or influence users’ inputs in online decision environments”. (Weinman et al., 2016)

2.2.2. Heuristics

Thaler and Sustein drew inspiration for the nudge notion from a behavioural economics paper. This article demonstrates how humans rely on a small set of heuristic concepts that simplify difficult tasks like estimating values and evaluating probability (Tversky & Kahneman, 1974).

The concept of heuristics is defined by Frimodig (2023) as "a mental shortcut or rule of thumb that simplifies decision-making and problem-solving. Heuristics often speed up the process of finding a satisfactory solution, but they can also lead to cognitive biases". The biases produced by these heuristics can be used to design nudges. The paper presents 3 common heuristics to explain their concept:

Representativeness: Individuals evaluate probabilities based on the degree to which an object or event is representative of or resembles a particular category. Essentially, they judge the likelihood of something based on how well it matches the stereotype or prototype of that category. (Tversky & Kahneman, 1974)

Availability: People judge the likelihood or frequency based on how easily instances or examples of that event or class can be brought to mind. If instances or examples come to mind readily, people tend to judge the event or class as more frequent or probable. (Tversky & Kahneman, 1974)

Adjustment and anchoring: When people start from an initial value or anchor and then adjust that value to arrive at a final answer, they do not move far enough away from the initial anchor. As a result, different starting points or anchors can lead to different estimates that are biased towards the initial value. (Epley & Gilovich, 2006)

2.2.3. Biases

While heuristics can be useful and efficient in many situations, they can also lead to systematic errors and deviations from rationality. Therefore, the use of heuristics can contribute to the emergence of biases (Tversky & Kahneman, 1974). These biases are exploited to create nudges capable of influencing decisions. Here are a few examples of biases that can be used to create nudges:

The decoy effect: This effect increases the attractiveness of an option by presenting another unattractive option that cannot be chosen logically. For example, when book buyers are presented with 2 options, $10 for a book in digital format and $20 for the same book in digital and hardcover format, the majority choose the digital version. If we present a third option that seems unreasonable, $20 for the hardcover version only, the majority will now choose the $20 option that offers both versions. (Weinman et al., 2016)

The scarity effect: People find scarce items more attractive than other items. Thus, by indicating that the availability of an option is limited, people are more likely to choose it. (Weinman et al., 2016). Backers of a hypothetical film production might choose between two rewards: $10 for a credit listing in the film or $50 for a DVD/Blu-ray disc of the film. 69% of supporters selected the low-price prize when it was the last one available, while 70% selected the high-price reward when it was the last one available.

The middle-option bias : People given 3 or more options will tend to choose the middle one. To prove this, researchers gave 3 groups of people 3 choices of sums to bet, telling them that they could bet one sum and have a chance of receiving double. One group was given a choice between $5, $10 and $15, another between $10, $15 and $20 and the last between $15, $20 and $25. In all 3 groups, the middle option was the most popular. (Weinman et al., 2016)

2.2.4. Nudge taxonomy

These biases and heuristics allow researchers to create a wide variety of nudges that will subconsciously influence consumers who are exposed to them, called nudgees. Numerous taxonomies for classifying and organizing nudge interventions have been proposed in response to the expanding body of research on these treatments. In the following we describe the most popular classifications using 2 different approaches.

Taxonomy by means

Münscher et al. (2016) divided nudges considering their means rather than ends, creating this taxonomy for creating successful interventions involving choice architecture. This taxonomy has the advantage of being inductively developed from documented cases of nudges, and the emphasis on intervention techniques makes it easier to build new testable interventions. In recent reviews on the impacts of nudges, the taxonomy of Münscher et al. has gained popularity due to its advantages (Ytreberg et al., 2023; Mertens et al., 2022; Wyse et al., 2021). Münscher et al. categorize nudges according to 3 main categories including 9 different techniques explained in table 2:

- The decision information category includes strategies in choice architecture that aim to display decision-relevant information in a way that doesn't change the alternatives themselves.

- The decision structure category changes the options that are available in the decision situation and the consequences of selecting it.
- The third category is the decision assistance which include techniques that aim at helping the customer to follow through with their intentions.

Table 2: Nudge taxonomy by Münscher et al (2016)

Category	Technique	Definition
Decision information	Translate information	Changing the format or presentation of information without changing the content
	Make information visible	Making information visible that is not apparent or readily available
	Provide social reference point	Providing information on other people's behaviour
Decision structure	Change option-related effort	Marginally changing the amount of effort the selection of an option requires
	Change choice default	Changing which options are pre-selected and what needs to be chosen actively
	Change option consequences	Linking micro-incentives to the consequences of the options
	Change range or composition of options	Making changes in the alternative options presented
Decision assistance	Provide reminders	Modifying the salience and the ease of access of options
	Facilitate commitment	Having participants committed to an option

This taxonomy being a mixture of different taxonomies proposed in previous research and being very exhaustive, it will be the taxonomy used throughout this thesis. But if nudges can have different means, they can also have different objectives.

Taxonomy by objective

Another categorization framework which considers means rather than ends is the one that Congiu & Moscati (2022) created dividing nudges into 3 categories according to their objective and not their means.

- The first category of nudges is intended to help the individual being nudged. These nudges are described as "pro-self" nudges by Hagman et al. (2015) because they "help individuals steer away from irrational behaviour which decreases their long-term well-being". (Hagman et al., 2015)
- By guiding the nudged individuals away from actions that might harm the common good, the second type of nudges principally aims to improve societal welfare. (Congiu & Moscati, 2022)
- The third category benefits primarily the nudgers (the company or the organisation) over the nudge (the consumer). It is more difficult to distinguish between a third-category nudge and a traditional marketing tactic like an add. (Congiu & Moscati, 2022)

At first glance, the use of nudging to limit returns of products purchased online falls into the latter category. However, in fact, while it primarily benefits the retailer (because, as we saw earlier, returns are very costly for the retailer), it also benefits society by reducing the greenhouse gas emissions associated with returns. It could even be argued that it partly benefits the consumer who, by making a more considered choice when making a purchase, saves time that would otherwise have been lost by having to deal with product returns, which can be sent back for a variety of reasons.

In the same spirit of classifying nudges according to their purpose, we can add the category of green nudge, whose aim is to encourage people to adopt more environmentally-friendly behaviour and thus is considered as a second category nudge by Congiu & Moscati (2022). Greens nudges can use all the means described by Münscher et al. (2016) to achieve their goals. This category is specifically developed just below.

2.2.5. Green nudge

The concept of "green nudging"—using nudges to encourage people to make decisions that lessen the negative consequences of their lifestyles and consumption on the environment—has only recently been studied by scholars. Green nudging, in a broader sense, is a component of research on Pro-Environmental Behaviour (PEB) that examines interventions aimed at lowering the negative environmental effects of human activities (White et al., 2019).

More and more studies are investigating this tool, which seeks to encourage consumers to choose the most environmentally-friendly options. For example, Loschelder et al. (2019) are testing which nudges are most effective in encouraging consumers to use a reusable cup rather than a disposable cup when buying coffee. Of the 4 messages tested based on: a dynamic norm, a static norm, an injunctive norm and a mix of static and injunctive norms, the one based on dynamic norm was clearly the most effective. It stated that "Our guests are changing their behaviour: More and more are switching from the to-go-cup to a sustainable alternative. Take part in this: Choose a sustainable cup and help to protect the environment". This information will prove very useful for our own study.

But the researchers' conclusions on the green nudge topic vary widely. For example, the study by Mirbabaie et al (2021), which tested the effectiveness of implementing a social norm nudge and a default nudge on a German fashion retail website to encourage consumers to choose "greener" products, concluded that it was not effective. Worse still, according to the study, the combination of the two nudges had a counterproductive effect. On the other hand, similar experiment by Cossatin et al. (2024) on the implementation of an information nudge on a fashion retail website concluded that it was effective.

According to Schubert (2017), there are three main types of green nudges that take advantage of different psychological desires: (i) green nudges based on people's desire to uphold a positive self-image through green behaviour; (ii) green nudges based on people's tendency to follow social norms and convictions; and (iii) green nudges that take advantage of people's propensity to choose default options.

Schubert (2017) also highlights that there is a chance that the effectiveness of many green nudges in changing behaviour is somewhat context-dependent. It might, for example, rely on how precisely framing is employed in the creation of green nudges as well as on the ideological or other predispositions of nudgees (such as their level of empathy or whether they have individualistic or communitarian views). This latter point might only be somewhat addressed when more sophisticated technologically based "personalized" nudges become available. As a result, green nudges should generally be viewed as enhancing rather than replacing conventional incentive-based initiatives.

One of the predispositions of the nudgees that is really relevant is the environmental sensitivity. Environmental sensitivity also called environmental awareness is a person's awareness, care, and duty for the environment based on his opinion of its importance to the nation (Hartmann et al., 2012). This concern might range from a general comprehension to a deep emotional commitment to environmental preservation (Schaffrin et al.,2011) and is crucial to ensure sustainable development (Cruz et al., 2022). According to Liu and Huang (2017), environmental awareness involves two processes. Being conscious of environmental change is the first of these processes; being concerned about environmental issues and working to find solutions is the second. It is associated with an interest in the environment and the presentation of behaviours to protect it (Singh et al., 2021). "Environmentally sensitive behaviours" are defined as acts taken by people and organizations to reduce environmental harm and provide solutions to environmental issues (Chao & Lam, 2011). Consequently, environmental consciousness fosters the growth of emotional ties and responsible behaviour toward one's living environment (Singh et al., 2021). This environmental sensitivity is used as a moderator of the effectiveness of a green nudge by Cardella et al. (2022), Von Zahn et al.(2022) and Mirbabaie et al. (2021).

2.3. Nudge to reduce product returns

The use of a nudge to reduce the rate of return, which can be considered a customer-based tool by Walsh & Möhring (2017), is currently a largely under-exploited area.There are so far, to the best of our knowledge, only 2 studies looking at the use of nudges to reduce product returns.

The first one from Von Zahn et al. (2022), seeks to demonstrate whether a simple nudge can reduce product returns and increase a company's profits. To achieve this, they used a double green nudge:

- A prompt that provided information on the environmental impact of goods returns when a customer checked their shopping basket.

- A reminder emphasizing that product returns are bad for the environment and asking customers to identify on a 5-point scale how committed they were to reducing product returns when the customer finished his purchase

Furthermore, they use cutting-edge machine learning techniques to actively embrace and capitalize on individual differences in how they react to being nudged in order to enhance the efficacy of the intervention. In this approach, they illustrate how machine learning and (green) nudging in online contexts are compatible. To administrate their nudge in a smart approach, they used data about the client (such as income or attitude towards environment) and about the product purchased.

Table 3: Result of the Von Zahn et al. (2022) study

Group	Observations	Return rate	Difference with no nudging	Profit	Difference with no nudging
No nudging	4921	23.33		8.65	
Naive green nudging	4999	22.23	-4.71%	9.48	+9.60%
Smart green nudging	4956	21.77	-6.69%	9.73	+12.49%

The use of the smart approach had a considerable impact on product returns. They discover that the initial basket value—that is, the amount of a customer's basket when they first check it—is by far the best indicator of the effectiveness of the nudge. Following this characteristic, the client's membership in an environmental group or lack thereof is the most crucial factor in determining the effectiveness of the nudge, which is followed by the private household's income and the number of products.

The limitation of this study is that it does not compare different types of nudge, but rather compares the effectiveness of this nudge with a traditional approach or smart approach.

The second study, by Ghose et al. (2023), aims to understand the effects of the various nudges used to increase sales on product returns. The research examines the financial impacts of two types of nudges on consumers' purchase and return behaviours: pressure-based interventions and self-assurance. The pressure-based messages were driven by quantity scarcity (“there are only X products left”), time scarcity (“the offer ends in x hours”) and social persuasion (“X people have bought this item in the last 24 hours”). The assurance-based message were designed to reassure customers about size (“The item especially fits your casual style nicely” or “Check out the perfect size for you”) and choice (“won’t it be your best choice?”). We can classify the first type of nudge as decision information nudge in the taxonomy explained above and the second type of nudge as decision assistance nudge.

The results showed that the pressure-driven nudges raise sales by 2.2 times compared to the no nudge purchasing rate, whereas assurance-based equivalents increase sales by 1.9 times. But when it came to product return rate, the assurance base nudge were more efficient because it decreased product returns by almost 69.3% in comparison to the levels attained with the pressure driven message. So, when product returns are taken into consideration, assurance nudges can be just as effective as pressure-driven counterparts. Another relevant finding is that the most efficient message to increase sales is the time scarcity message, but it is also the message that raises the return rate the most.

The limitation of this paper is that it does not study the effectiveness of nudge aimed at reducing product returns but rather studies the influence of classic nudge aimed at increasing sales on the return rate.

2.2.4. Conclusion of the literature review

The topic of product returns is a nuanced and extensively explored subject in the existing literature. Researchers have delved into various aspects, beginning with an in-depth analysis of the reasons behind product returns. The findings in this area reveal a plethora of diverse factors contributing to the return of products, illustrating the complexity of consumer behaviour and decision-making.

Efforts to mitigate the quantity of returned products have been a focal point of scholarly inquiry. Many studies have been dedicated to proposing solutions, with a predominant emphasis on the leniency of return policies. However, the literature reveals a lack of consensus among researchers regarding the most effective strategies to implement. An illustrative example is the contentious issue of reimbursement for returned products, where differing viewpoints exist on the optimal policy that would concurrently increase profitability.

In addition to conventional approaches centred around return policies, an alternative solutions could be the application of "nudges" to influence consumer behaviour. Despite being a relatively new concept, the literature on nudges is extensive, encompassing various domains. Surprisingly, few studies have sought to connect the theory of nudges with the specific objective of reducing product returns. Notably, the limited existing research in this area highlights the potential of nudges but only scratches the surface of possibilities.

This dissertation aims to contribute to the existing body of knowledge by extending the exploration of nudges as a means to address the challenge of product returns. The focus will be on testing additional nudges designed to influence consumer decisions in the context of online purchases. Furthermore, the effectiveness of two distinct nudges will be compared, providing valuable insights into the nuanced dynamics of consumer behaviour and its implications for reducing the rate of product returns. Through this research, we seek to expand understanding in this domain and offer practical insights for businesses aiming to optimize their return management strategies.

The research question we propose for this dissertation is as follows:

“What is the impact of an information nudge and a social reference nudge on a consumer's intention to return a product purchased online?”

3. Modele and hypothesis

3.1. Hypothesis 1 : Effectiveness of 2 types of nudge

The information nudge aims to fulfil the gap of a not apparent or not readily available information by giving this information that can changed their decision to people (Schubert, 2017; Thaler & Sustein, 2008). Consumers are increasingly taking the ecological impact of their purchases into account in their purchasing decisions when the information is easily available (La Rosa & Johnson, 2021). Against this backdrop, several studies examine the impact of an information green nudge aiming to encourage pro-environmental behaviour and their results show a real efficiency of this kind of nudge. The desired results of these nudge are varied green behaviour such as the selection of voluntary green power plants (Cardella et al., 2022), the adoption of a organic farming by farmers (My et al., 2022), the diminution of meat consumption (Dannenberg & Weingärtner, 2023; Spaargaren et al., 2013) or the rise of the willingness to pay for a bio-based packaging (Wensing et al., 2020).

Therefore, we hypothesize:

> **H1.1 Implementing a nudge providing information will significantly reduce the consumer's intention to return a product.**

A person behaviour is greatly influenced by his perception of what other people do, either directly or indirectly through information provided by a third party (Nolan et al., 2008). Social norms work like nudges by drawing on the power of social influence and peer pressure. Several studies explored the effectiveness of social norm nudge to motivate people to adopt different pro-environmental behaviour: the rise of sustainable transportation behaviour (Kormos et al., 2015), the environmental conservation in hotels (Goldstein et al., 2008) ; the household energy conservation (Schultz et al., 2007; Nolan et al., 2008). These various experiments have all concluded that social norm nudges were highly effective. Nolan et al. (2008) even conclude this kind of nudge was more efficient than the information nudge.

Thus, we hypothesize:

> **H1.2 Implementing a social norm nudge will significantly reduce the consumer's intention to return a product.**

3.2. Hypothesis 2: The mediating effect of the perceived responsibility of consumers

According to Luchs, Brower & Chitturi (2012), in the sustainable consumption choice, the consumer often face with trade-offs between choices that meet self-oriented consumptions goals (price, ease of use, …) and choices that are perceived as ethically superior and especially more sustainable. According to Luchs et al. (2012) findings, behaviour is positively influenced by both broad attitudes toward sustainability and a sense of personal accountability for sustainable consumption. Put another way, consumers who exhibit both a strong sense of personal responsibility about environment and a favourable attitude toward sustainability are more likely to engage in sustainable consumption behaviours.

When information and social norms nudges are designed to remind consumers that product returns have an environmental impact, we expect that they influence consumers' perception of environmental responsibility and that this will affect the decision as to whether or not to return the product. Thus, we hypothesize:

> **H2.1 The effect of a nudge providing information on the consumer's intention to return a product is mediated by perceived personal responsibility for sustainable consumptions.**
>
> **H2.2 The effect of a social norm nudge on the consumer's intention to return a product is mediated by perceived personal responsibility for sustainable consumptions.**

3.3. Hypothesis 3: The moderating effect of the environmental sensitivity

Numerous studies have examined the link between consumers' sensitivity to the environment and their purchasing behaviour. There is a positive correlation between environmental awareness and the purchase of green products (Kim & Choi, 2005; Alkaya et al., 2016). According to Hamzah et al. (2021), the environmental awareness of consumers is a moderator variable between green marketing and the consumer purchasing intention. Yayla et al. (2021) also concluded that Environmental sensitivity positively affects the ecological product purchasing intention. There are also evidences that the use of information nudges work better with people who have a better attitude about the environment than on other people. For example, the study of Cardella et al. (2022) demonstrated that an information nudge encouraging people to choose a green plan raised by the adoption of the green plan by 34% among the customer who are "more environmental" friendly and only by 8,5 % among people who are "less environmental" friendly.

We can therefore hypothesize:

> **H3.1: The effectiveness of an information nudge in reducing the intention to return a product is higher (lower) if the consumer has a high (low) sensitivity to environmental causes.**
>
> **H3.2: The effectiveness of a social norm nudge in reducing the intention to return a product is higher (lower) if the consumer has a high (low) sensitivity to environmental causes.**

3.4. Experimental Conceptual model

All these hypotheses can be summarized in the following graph:

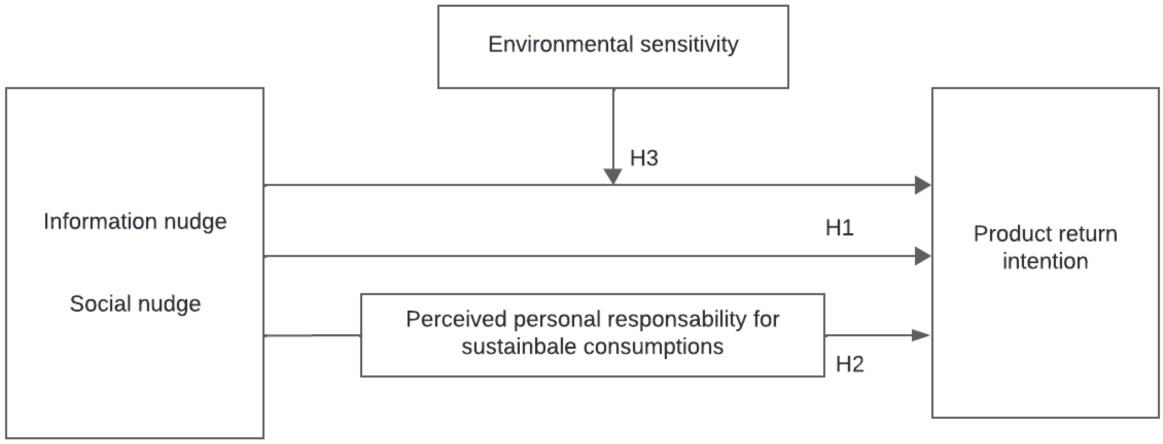

Figure 2: Experimental conceptual model

4. Methodology

The methodology use for the experimentation is adapted from the Yayla et al. (2012) paper to fit with the online context of the thesis.

4.1. Research instrument

In this report, we decided to use a quantitative approach to test the various hypotheses. This method is appropriate in our case because it allows us to reach the largest possible sample. The tool chosen to create the form is called Qualtrics. This tool can be used to create online forms that are fairly comprehensive and easy to analyse. The questionnaire was distributed on social networks and by email. The between subject method was chosen for this study because it minimised learning and transfer across condition.

4.2. Sampling and data collection

For the purposes of this study, the target population is the population as a whole. Nowadays, all categories of the population are likely to make online purchases and therefore potentially to make returns on these purchases. As this questionnaire is distributed essentially via the Internet, it will probably not reach the population that does not use internet at all. This problem of representativeness is not crucial as this population is not directly concerned by returns of products bought online. In addition, the majority of respondents to the questionnaire are probably Belgian, as the questionnaire is mainly distributed via Belgian social networking accounts. We calculated the minimum sample size for this statistical test to have an alpha level of 0.05 and a power of 0.8 using the G* power software. This required sample size is 158 participants (see Appendix 1).

The sampling used in this dissertation is non-probabilistic, i.e., it is the respondents who choose to complete the survey and not people chosen at random beforehand. In order to obtain respondents quickly and easily, it was simpler to use respondents who were available when the survey was distributed, so this sample is convenience sampling, but this choice could lead to self-selection bias.

4.3. Stimulus development

In order to carry out the statistical tests, the example of an online purchase of clothing is used. This choice is explained by the fact that this is the type of product that is most often returned when purchased online (Trapnell, 2023).

In order to reduce the noise caused by people's personal tastes and gender differences, a simple white t-shirt was chosen as the product to be tested. The neutrality of this t-shirt means that we can imagine it appealing to people of both sexes and all ages. As a white t-shirt has no particular style, we can imagine that the tastes of potential respondents have less influence and that they focus mainly on its function as clothing.

The design of the Amazon e-commerce site was chosen because 82% of French-speaking Belgians, who make up the majority of survey respondents, have already used Amazon at least once (Mikolajczak, 2022). We can therefore deduce that the layout of a shopping page is familiar to the vast majority of respondents. This design therefore minimizes the chances of the shopping page being misunderstood, which could distort the results.

All participants will be asked to look at an image: "Let's suppose you want to buy a T-shirt on an e-commerce platform. Please take a close look at the following image showing the site's purchase page." Followed by a stimuli display with one of 3 scenarios: without nudge, with information nudge and with norm social nudge (see Figure 3,45. The participant is then asked to give his or her level of approval for various items. First the items measuring the intention of returning the product then the CFRS items followed by a question to check the participant's attention and whether they have seen the nudge on the previous page.. The survey ends with some demographic questions and the items measuring environment sensibility. The survey is presented in full in Appendix 2.

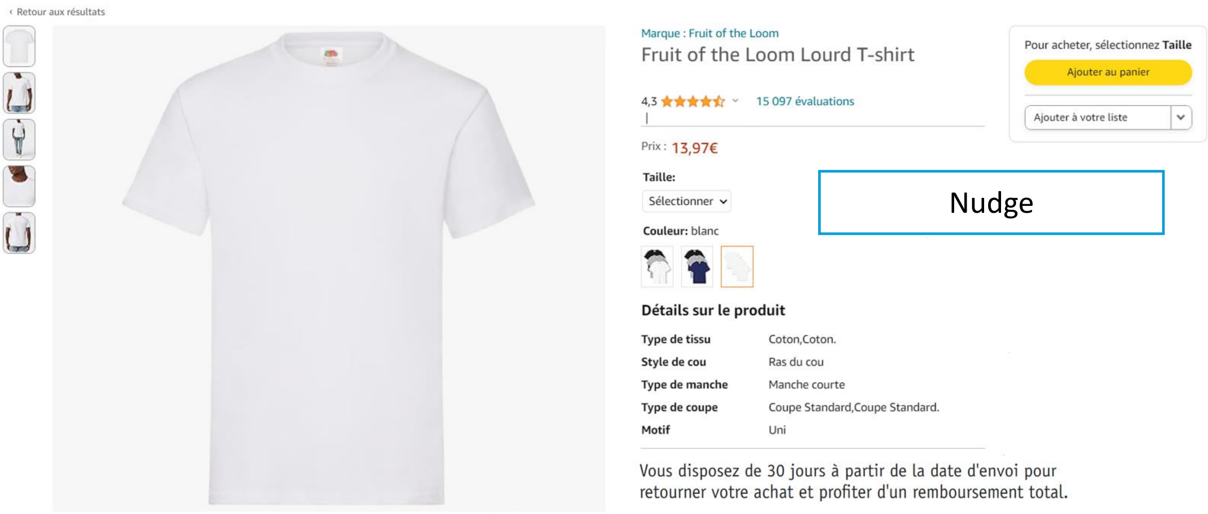

Figure 3: Display presented in the survey without nudge

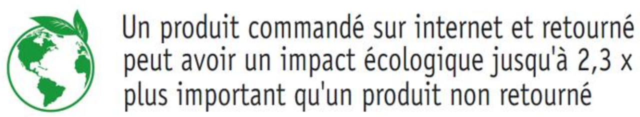

Figure 4: Information nudge tested

Figure 5: Social nudge tested

Information nudge

The information nudge delivers very simple and not too technical information so that all participants understand it, whatever their level of knowledge of ecological issues. The information comes from an article by Petit (2024) which states that "A product ordered on the internet and returned can have an ecological impact up to 2.3 times greater than a product not returned".

Social nudge

While several studies have proven the effectiveness of a social norm nudge that allows consumers to compare their own behaviour in terms of ecological choices with the behaviour of others, some studies have shown that such a nudge can have a negative effect on consumers who already behave more responsibly than their neighbours. A “boomerang effect” can cause people who are already doing better than the average to relax their efforts, as they realise that they are making more effort than the average without necessarily being rewarded (Cialdini et al., 2006; Schulz et al., 2007). To counteract this boomerang effect Demarque et al. (2015) suggest emphasizing the trend that we want to highlight without necessarily mentioning precise figures, so that the minority acting correctly appears to be less of a minority. With this in mind, the social norm nudge that we test in this thesis is based on the trend whereby more and more people have become aware of the environmental impact of product returns and are trying to reduce them without any figures. The social nudge we use is based on the nudge model that worked best in the paper by Loschelder et al. (2019), namely one based on dynamics but presenting no numbers.

4.4. Relevant variables and their measurement

In order to measure the different variables used in our model, we use 5 items per variable, which are statements to which the participants must give their level of agreement on a Likert scale with 7 levels: "Strongly disagree"; "Disagree"; "Somewhat disagree"; "Neither agree nor disagree"; "Somewhat agree"; "Agree"; "Strongly agree". This scale provides nuanced quantitative results with a neutral choice and allows these figures to be used as continuous variables. The items all come from scientific studies and were slightly adapted to correspond more closely to the situation in which the participants were asked to imagine themselves (i.e. buying a T-shirt).

To test the consistency of these different items, we calculate the Cronbach’s alpha coefficient that measures the internal consistency, or reliability, of a set of survey items by quantifying the level of agreement on a standardized 0 to 1 scale. This test allows us to conclude that the items are fairly consistent with each other, as all Cronbach's alphas are greater than 0.8 (see Appendix 3).

To confirm the consistency of our items, we also use the Kaiser-Meyer-Olkin (KMO) index, which measures the proportion of variance among variables that might be common variance.

Once again, the results show good consistency, with values above 0.8 each time (see Appendix 4).

Table 4: Summary of items used for variables

Variable	Item	Wording	Cronbach's alpha	KMO index	Reference
Environmental sensitivity	ES1	It frustrates me that official institutions do not take measures to control environmental pollution.	0.859	0.825	Adapted from (Yayla et al., 2021)
	ES2	I get angry when I think about the environmental pollution caused by industrial factories.			
	ES3	Climate warming worries me.			
	ES4	I am concerned about the effects of polluted air on me and my family.			
	ES5	I'm afraid that if we continue to pollute, the world will become uninhabitable.			
Consumer's felt responsibility for sustainability	CFRS1	I feel obligated to try to implement sustainable practices where appropriate.	0.831	0.815	Adapted from Luchs & Miller (2015)
	CFRS2	It's up to me to encourage progress in terms of ecology.			
	CFRS3	I feel a bit obliged to question my practices to make them more ecological.			
	CFRS4	I feel a personal sense of responsibility to be more sustainable in my choices.			
	CFRS5	Correcting sustainability related problems is not really my responsibility. (*this variable is inverted)			
Online return intention	RI1	Even if the return process is troublesome, I will choose to return.	0.888	0.866	Adapted from Lv & Liu (2022)
	RI2	I will return the t-shirt if it is unsuitable.			
	RI3	As long as the product doesn't fit, I intend to return it.			
	RI4	I think it is the right decision to return the t-shirt if it doesn't suit me.			
	RI5	Even if the t-shirt is cheap, I will choose to return it if I don't like it.			

5.Results

5.1. Demographics

The survey was open from 25 April to 7 May 2024 and was completed by 270 respondents, of whom only 211 were considered valid because they correctly answered the first manipulation check, a question verifying attention (16 people failed this test) and the second manipulation check, a question verifying whether they had seen the nudge presented (43 people failed this test).

The table below shows the distribution of the different demographic data received between the groups that received different nudges.

Table 5: Summary of demographics

		No nudge (N=76)	Social nudge (N=69)	Information nudge (N=66)
Gender (in %)	Male	47	43	33
	Female	53	57	66
Age	Min	18	20	19
	Mean	33	35	37
	Median	28	29	35
	Max	69	61	73
Highest level of education (in %)	Primary school	1	0	2
	High school	24	19	21
	Bachelor’s	30	49	41
	Master’s	45	30	35
	PhD	0	2	1
Currently employed	Yes	67	76	79
	No	33	24	21

5.2. Testing H1

In order to verify whether hypothesis 1, according to which the implementation of a nudge reduces the intention to return the product, we use a linear regression. As the dependent variable is a quantitative variable (the average intention to return) and the independent variable a nominal variable (the type of nudge used), the use of "dummy" variables transforming nudge categories into binary values is necessary. This regression studies the effect of the presence of each of the 2 nudges studied in comparison with a situation where no nudge is present.

The results shown in figure X show that the information nudge has a real effect on the intention to return. Its presence reduces the intention to return by 0.978 points on a scale of 7, representing a reduction of 13.97%. This result is very significant because it has a p-value of less than 0.001.

On the other hand, social nudge also has an effect, reducing the intention to return by 0.441 points, corresponding to a reduction of 6.3%. However, this result should be treated with caution, as its p-value of 0.053 is slightly above the acceptability threshold used by most scientific papers (0.05) but below the threshold of 0.1 at which the hypothesis is necessarily rejected. The regression model has an R^2 of 0.08 (see table X), which means that 8% of the return intention score can be explained by the presence or absence of a nudge.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	5,147	,156		32,921	<,001
	is social nudge	-,441	,227	-,147	-1,945	,053
	is info nudge	-,978	,229	-,321	-4,263	<,001

a. Dependent Variable: Moyenne return intention

Figure 6: Coefficient of the regression for hypothesis 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,283[a]	,080	,072	1,36309

a. Predictors: (Constant), is info nudge, is social nudge

Figure 7: Summary of the regression for hypothesis 1

We need to check whether the errors in the regression are normally distributed in order to verify that the regression is correct. The Shapiro-Wilk test shows that the errors are indeed normally distributed, with a consistency of 0.09 (see Figure 8). We can therefore conclude that the regression is correct.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Unstandardized Residual	,075	211	,006	,982	211	,009

a. Lilliefors Significance Correction

Figure 8: Normality test of errors

Another possibility for testing hypothesis 1 is to use an ANOVA analysis, but this requires the data to meet 2 assumptions: the homogeneity of variances, which can be tested with the Levene test, and the normal distribution of values, which can be tested with the Shapiro-Wilk test. Our data met the first condition but not the second (see Appendix 6), so an ANOVA analysis could produce biased results making the linear regression therefore more appropriate.

Nevertheless, we are still testing the ANOVA analysis to check whether the results obtained with linear regression are consistent. This analysis concludes that there is indeed a difference in mean return intention between the groups having received different nudges (with a p-value of less than 0.001) (see Appendix 7) . Next, Tukey's post hoc test enabled us to see which pairs of groups were significantly different from each other (see Appendix 8). According to this test, the presence of the information nudge effectively reduces return intention by 0.977 points, with a p-value of less than 0.001. This test also attributes a 0.44 point reduction in return intention to the social nudge, but here again the p-value (0.129) is too high to consider this result significant. The fact that the regression analysis and the Tukey test give the same value suggests that this value of 0.44 indicates a low but actual effectiveness of social nudge.

5.3. Testing H2

The second hypothesis to be tested is that the relationship between the presence or absence of a nudge and the reduction in the intention to return is partly explained by a mediating variable: the perceived personal responsibility for sustainable consumption. To do this, we use the macro PROCESS, which has been added to SPSS in order to carry out mediation and moderation analyses. This extension allows us to see the direct, indirect and total effects that could provide a more detailed understanding of how the nudge works. Unfortunately, the results are not conclusive, as the figures obtained to explain the link between the independent variable and the mediating variable are very far from significant, with a p-value of p=.30 for social nudge and p= .61 for information nudge (as shown in figure 10 and appendix 9). It is therefore not possible to state that the presence of one of these nudges increases perceived personal responsibility for green consumption. The indirect effect of the mediating variable calculated by SPSS has a bootstrap confident interval of 0 for both information nudge and social nudge. Consequently, the indirect effect cannot be proved and the hypothesis that this variable is a mediating variable must be rejected.

```
OUTCOME VARIABLE:
 CFRS

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1057      ,0112     1,1525     1,1739     2,0000   208,0000      ,3112

Model
             coeff         se          t          p       LLCI       ULCI
constant    4,7842      ,1231    38,8501      ,0000     4,5414     5,0270
social n     ,1839      ,1785     1,0302      ,3041     -,1680      ,5358
info n      -,0933      ,1806     -,5165      ,6060     -,4494      ,2628

Standardized coefficients
        coeff
X1      ,1712
X2     -,0868

**************************************************************************
OUTCOME VARIABLE:
 RI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3168      ,1004     1,8264     7,6985     3,0000   207,0000      ,0001
Model
              coeff         se          t          p       LLCI       ULCI
constant     6,0434      ,4454    13,5674      ,0000     5,1652     6,9215
social n     -,4064      ,2253    -1,8039      ,0727     -,8506      ,0378
info n       -,9951      ,2275    -4,3737      ,0000    -1,4437     -,5466
CFRS         -,1873      ,0873    -2,1457      ,0331     -,3594     -,0152


************************** TOTAL EFFECT MODEL ****************************
OUTCOME VARIABLE:
 RI
Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2835      ,0804     1,8580     9,0883     2,0000   208,0000      ,0002

Model
              coeff         se          t          p       LLCI       ULCI
constant     5,1474      ,1564    32,9205      ,0000     4,8391     5,4556
X1           -,4408      ,2267    -1,9450      ,0531     -,8877      ,0060
X2           -,9777      ,2293    -4,2629      ,0000    -1,4298     -,5255

************** TOTAL, DIRECT, AND INDIRECT EFFECTS OF X ON Y **************

Relative total effects of X on Y
       Effect         se          t          p       LLCI       ULCI       c_ps
X1     -,4408      ,2267    -1,9450      ,0531     -,8877      ,0060     -,3116
X2     -,9777      ,2293    -4,2629      ,0000    -1,4298     -,5255     -,6911

Omnibus test of total effect of X on Y
    R2-chng          F        df1        df2          p
      ,0804     9,0883     2,0000   208,0000      ,0002
----------
Relative direct effects of X on Y
       Effect         se          t          p       LLCI       ULCI      c'_ps
X1     -,4064      ,2253    -1,8039      ,0727     -,8506      ,0378     -,2873
X2     -,9951      ,2275    -4,3737      ,0000    -1,4437     -,5466     -,7035

Omnibus test of direct effect of X on Y:
    R2-chng          F        df1        df2          p
      ,0834     9,6000     2,0000   207,0000      ,0001
----------
Relative indirect effects of X on Y

 Typeofnu    ->    CFRS        ->    RI

       Effect     BootSE   BootLLCI   BootULCI
X1     -,0344      ,0384     -,1248      ,0280
X2      ,0175      ,0407     -,0622      ,1061

Partially standardized relative indirect effect(s) of X on Y:

 Typeofnu    ->    CFRS        ->    RI

       Effect     BootSE   BootLLCI   BootULCI
X1     -,0243      ,0269     -,0872      ,0194
X2      ,0124      ,0286     -,0430      ,0747
```

Figure 9: Output of the linear regression with mediation

5.4. Testing H3

The third hypothesis to be tested is the moderating effect of environmental sensitivity on the effectiveness of the 2 nudges in reducing return intention. As for hypothesis 2, we use the PROCESS macro in SPSS but unlike mediation analysis, we test the effect of moderation on one nudge at a time.

When we perform this test with the information nudge, we see that the interaction coefficient is -.374 with a p-value of p=.06, which is above the .05 threshold but which may still indicate that the effect of the nudge on the intention to return changes according to the level of the moderator (the environmental sensitivity). To go further, the Johnson-Neyman test can be used to identify the specific values of the moderator for which the effect of the independent variable on the dependent variable is significant. Using this test, we can see that when the environmental sensitivity is below 4.15, the effect of the nudge is not significantly proven, whereas above 4.15, the nudge does have an effect on the intention to return. In conclusion, even if the p-value of the overall interaction is slightly greater than 0.05, the results of the Johnson-Neyman test indicate that there are values of the moderator variable for which the effect of the independent variable on the dependent variable is significant. We cannot therefore totally reject the hypothesis, but neither can we totally confirm it. On the other hand, we can state that from a minimum level of 4.15 for environmental sensitivity, the more sensitive a person is to the environment, the more they will be influenced by nudge.

Model Summary

R	R-sq	MSE	F	df1	df2	p
,3860	,1490	1,7028	8,0545	3,0000	138,0000	,0001

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,6110	,7603	6,0648	,0000	3,1077	6,1143
isinfonu	,9491	1,0537	,9007	,3693	-1,1344	3,0326
ES	,1003	,1394	,7195	,4730	-,1753	,3759
Int_1	-,3742	,1977	-1,8928	,0605	-,7652	,0167

Figure 10: Output of the linear regression with moderation for information nudge

Conditional effect of focal predictor at values of the moderator:

ES	Effect	se	t	p	LLCI	ULCI
1,6000	,3503	,7474	,4687	,6400	-1,1275	1,8281
1,8700	,2493	,6966	,3579	,7210	-1,1280	1,6266
2,1400	,1482	,6462	,2294	,8189	-1,1294	1,4259
2,4100	,0472	,5963	,0791	,9370	-1,1319	1,2262
2,6800	-,0538	,5471	-,0984	,9217	-1,1356	1,0279
2,9500	-,1549	,4987	-,3106	,7566	-1,1410	,8312
3,2200	-,2559	,4515	-,5669	,5717	-1,1487	,6368
3,4900	-,3570	,4058	-,8797	,3806	-1,1594	,4454
3,7600	-,4580	,3622	-1,2645	,2082	-1,1742	,2582
4,0300	-,5591	,3216	-1,7384	,0844	-1,1950	,0768
4,1480	-,6032	,3051	-1,9773	,0500	-1,2065	,0000
4,3000	-,6601	,2852	-2,3144	,0221	-1,2241	-,0961
4,5700	-,7612	,2549	-2,9860	,0033	-1,2652	-,2571
4,8400	-,8622	,2330	-3,7000	,0003	-1,3230	-,4014
5,1100	-,9632	,2221	-4,3372	,0000	-1,4024	-,5241
5,3800	-1,0643	,2237	-4,7575	,0000	-1,5066	-,6219
5,6500	-1,1653	,2376	-4,9040	,0000	-1,6352	-,6955
5,9200	-1,2664	,2619	-4,8354	,0000	-1,7842	-,7485
6,1900	-1,3674	,2940	-4,6518	,0000	-1,9487	-,7862
6,4600	-1,4685	,3316	-4,4290	,0000	-2,1240	-,8129
6,7300	-1,5695	,3730	-4,2075	,0000	-2,3071	-,8319
7,0000	-1,6706	,4172	-4,0041	,0001	-2,4955	-,8456

Figure 11: Johnson-Neyman analysis of the moderation effect with information nudge

For social nudge, the interaction coefficient is even less significant with a p-value of only p=.083. When we carry out the Johnson-Neyman test, we see that the nudge only has an effect on the intention to return if the person has an environmental sensitivity greater than 5.5. In summary, although we cannot confirm the hypothesis of a statistically significant overall interaction at the .05 level (p =.083), the results of the Johnson-Neyman analysis show that there is a significant interaction for high levels of environmental sensitivity (above 5.5). This means that there is a also a conditional moderation and the effect of social nudge on intention to return is significant for a specific subgroup of the study population.

Model Summary

R	R-sq	MSE	F	df1	df2	p
,2275	,0517	1,6821	2,5643	3,0000	141,0000	,0571

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,6110	,7557	6,1020	,0000	3,1171	6,1049
SocialN	1,4209	1,0876	1,3065	,1935	-,7292	3,5710
ES	,1003	,1385	,7240	,4703	-,1736	,3742
Int_1	-,3485	,1995	-1,7470	,0828	-,7430	,0459

Figure 12: Output of the linear regression with moderation for social nudge

Conditional effect of focal predictor at values of the moderator:

ES	Effect	se	t	p	LLCI	ULCI
2,0000	,7238	,7010	1,0326	,3036	-,6620	2,1096
2,2500	,6367	,6537	,9740	,3317	-,6556	1,9290
2,5000	,5495	,6068	,9056	,3667	-,6501	1,7492
2,7500	,4624	,5605	,8250	,4108	-,6457	1,5705
3,0000	,3753	,5148	,7289	,4672	-,6425	1,3930
3,2500	,2881	,4700	,6131	,5408	-,6410	1,2173
3,5000	,2010	,4263	,4715	,6380	-,6418	1,0438
3,7500	,1139	,3841	,2964	,7673	-,6455	,8732
4,0000	,0267	,3440	,0777	,9382	-,6533	,7067
4,2500	-,0604	,3067	-,1970	,8441	-,6668	,5459
4,5000	-,1475	,2735	-,5395	,5904	-,6882	,3932
4,7500	-,2347	,2460	-,9540	,3417	-,7210	,2516
5,0000	-,3218	,2263	-1,4223	,1572	-,7691	,1255
5,2500	-,4090	,2165	-1,8892	,0609	-,8369	,0190
5,3009	-,4267	,2158	-1,9769	,0500	-,8534	,0000
5,5000	-,4961	,2179	-2,2764	,0243	-,9269	-,0653
5,7500	-,5832	,2304	-2,5309	,0125	-1,0388	-,1277
6,0000	-,6704	,2524	-2,6563	,0088	-1,1693	-,1715
6,2500	-,7575	,2815	-2,6908	,0080	-1,3140	-,2010
6,5000	-,8446	,3159	-2,6738	,0084	-1,4691	-,2201
6,7500	-,9318	,3540	-2,6323	,0094	-1,6316	-,2320
7,0000	-1,0189	,3947	-2,5815	,0109	-1,7992	-,2386

Figure 13: Johnson-Neyman analysis of the moderation effect with social nudge

5.5. Hypotheses summary table

Table 6: Summary of hypotheses results

Hypothesis	Prediction	Result
H1.1	Implementing a nudge providing information will significantly reduce the consumer's intention to return a product.	Supported
H1.2	Implementing a social norm nudge will significantly reduce the consumer's intention to return a product.	Supported with a 5,3 % significance
H2.1	The effect of a nudge providing information on the consumer's intention to return a product is mediated by perceived personal responsibility for sustainable consumptions	Rejected
H2.2	The effect of a social norm nudge on the consumer's intention to return a product is mediated by perceived personal responsibility for sustainable consumptions.	Rejected
H3.1	The effectiveness of an information nudge in reducing the intention to return a product is higher (lower) if the consumer has a high (low) sensitivity to environmental causes.	Neither rejected nor accepted
H3.2	The effectiveness of a social norm nudge in reducing the intention to return a product is higher (lower) if the consumer has a high (low) sensitivity to environmental causes.	Neither rejected nor accepted

6. Theorical implication and managerial recommendations

6.1. Implications

Reducing product returns is a major issue for online retailers, and companies will increasingly need to find effective ways of avoiding them. For the moment, reducing the leniency of return policies is a means of avoiding returns that is still hotly debated among researchers. Some conclude that it is effective (Bower & Maxham, 2012; Schulman et al., 2010; Pei et al., 2014), while others conclude that it necessarily leads to a reduction in turnover and that the reduction in profits exceeds the savings made by avoiding returns (Altug et al., 2016; Shang et al., 2018; Lantz & Hjort, 2013). The use of nudges seems to be a solution that does not have the disadvantage of reducing turnover while having a real impact.

The literature on nudges aimed directly at reducing consumers' intention to reduce product returns is fairly sparse. In fact, we found only one study dealing with the direct use of nudges for this purpose. This study of Von Zahn et al. (2023) only tested an information nudge, similar to ours as it is also based on the argument of the ecological impact of product returns because as product returns are harmful for the environment, the ecological impact appears to be a logical argument for consumers to forgo a return (Calma, 2019). This paper also tested a machine learning system to determine 'smartly' the administration of this green nudge on the individual level to optimize its effectiveness. It used certain information available about the customer, such as their IP address and basket value, to understand on which group of people the nudge worked best on and thus to fine-tune the targeting of the nudge. This smart approach appeared to be more effective than the naïve approach.

In order to add to this limited literature and to continue the discoveries in the field of green nudges for product returns, we chose to test 2 different nudges to check if the information nudge is really the best option for this purpose but we did not use the smart approach of Von Zahn et al. (2023). These 2 nudges are based on the same ecological impact argument but present it in different ways. We also distinguished ourselves by trying to understand how these nudges work by testing a moderator variable and a mediator variable. Whereas the study by Von Zahn et al (2023) used objective variables such as users' income, the purchase value of the basket, the number of items purchased, etc. as moderating variables to understand who to administer the nudges to, we tested a more subjective moderating variable, namely environmental sensitivity.

Although some studies (Loschelder et al., 2019; Nolan et al., 2008; Münscher et al., 2016) consider the social nudge to be one the most effective nudge, our results do not allow us to fully conclude that it is effective in reducing product returns. Even if its effectiveness is probable, it is fairly low. Greens nudges cannot be seen as a homogeneous category and what works for one particular ecological goal will not necessarily work for another specific goal. However, the fact that only one social comparison nudge was tested is a limitation because we cannot conclude whether social nudges as a whole are ineffective or whether it is only the message tested that is ineffective. In this study, we chose to use a message that was deliberately vague because we wanted to avoid the boomerang effect that a social nudge can produce (Demarque et al., 2015) and it was therefore based on the nudge model that worked best in the paper by Loschelder et al. (2019). The nudge presented a dynamic without giving concrete figures, which may have been misperceived by respondents.

On the other hand, the information nudge proved to be quite effective, reducing the intention to return by 14%, which is even more than the only study that tested an information nudge for the same purpose, which found a reduction of 4.7% (Von Zahn et al., 2023). The information nudge we tested presented a single piece of clear and concise information. Its effectiveness and ease of implementation make it a promising avenue for researchers and companies. According to Mariotti et al (2023), to be effective, the design of an information nudge must focus on a specific target group and present a signal that is credible for this target group. This approach was also used by Von Zahn et al (2023), who concluded that nudges were more effective if they were well targeted. This approach to targeting groups receiving nudges was not tested as part of this dissertation, but it is conceivable that this approach could be explored in the future in order to improve the effectiveness of nudges. To achieve this, it is important to understand how nudges operate.

The mechanisms through which these two nudges operate remain somewhat unclear, according to this thesis' results, because our test of the variable we thought would be a mediator—namely, personal responsibility to consume more sustainably—did not yield conclusive results. Therefore, at this stage, we do not know if there is a mediating variable between the presence of a nudge and the intention to return products.

The tested moderating variable were not totally proved effective but our analysis showed that the information nudge was effective on people with an environmental sensitivity of at least 4.15 on a scale of 7 and at least 5.5 for the social nudge. It made sense to think that sensitivity to environmental causes would enhance the effectiveness of nudges, given their ecological basis and the fact that it is used as a moderating variable by Cardella et al. (2022), Mirbabaie et al. (2021), Hamzah et al. (2021) and Yayla et al. (2021). Even if it has not entirely been confirmed as a moderating variable in our case, we can imagine that they could be used at least in part to develop target groups for administering nudges, as suggested by Von Zahn et al (2023).

There are several potential explanations for why environmental sensitivity did not act perfectly as a moderator in our model. According to Carrel & Caldara (2023), greens nudges can be classified into 2 categories, those trying to improve the perceived feasibility of the pro-environmental behaviour by consumers (the how) and those trying to improve the desirability of pro-environmental behaviour (the why). The two nudges we have created are desirability nudges, the social nudge being in the sub-category of social desirability nudges and the information nudge being in the sub-category of emotional activation nudges. And according to Carrel & Caldara (2023), this type of nudge less effective and less moderated by environmental sensitivity than feasibility nudge.

A second explanation for why environmental sensituvity does not play a greater moderating role is that several studies show a significant difference between sensitivity to the environment and pro-environmental behaviour (Fu et al., 2020 ; Kollmuss & Agyeman, 2002 ; Shen et al., 2024). Fu et al (2020) explain this discrepancy by the fact that the obstacles to choosing PEB are stronger than the motivating factors. Kollumuss & Agyeman (2002) stress the importance of the inertia of old behaviour patterns and Shen et al (2024) explain that the adoption of PEB is not really moderated by environmental sensitivity but is rather influenced by climate change health risk perception. This perspective opens up the possibility of a third explanation for the weakness of moderation in our model: the relationship between environmental sensitivity and response to nudges could be more complex than anticipated, possibly non-linear or influenced by other unexamined variable. The search for explanatory variables, whether they moderate or mediate the effectiveness of nudges aimed at combating product returns, is an area that has yet to be explored.

6.2. For business

For retailers, implementing an information nudge to reduce product return rates could be highly beneficial. Nudges are easy to implement, especially online, with minimal costs and little risk of reducing turnover, unlike stricter return policies.

However, much remains to be understood about effectively using nudges in this context. If this thesis prove that the information nudge is effective, given the wide variety of available nudges, it would be prudent to test many of them to identify the most effective ones. For instance, default choice nudges could automatically select the option "I give up on returning my product," or change option consequences nudges could offer incentives to choose not to return a product. The defaults choice nudges have already been tested with the aim of encouraging greener choices and have proved to be very effective (Kaiser et al., 2020; Toft et al., 2014). Additionally, it is crucial to experiment with different versions of the two nudges tested in this paper by modifying the messages to determine the most effective approaches.

Although testing all these options can be time-consuming and laborious, large retail platforms have the advantage of vast user bases, allowing for extensive experimentation. Beyond testing different nudges, it is also essential to understand the mechanisms behind their effectiveness. Research into moderating and mediating variables could be key to enhancing nudge efficacy. Potential moderating variables include the type of product purchased, purchase frequency, usual return rate, product cost, desire to act more ecologically, and purchasing power. Furthermore, as mentioned by Schubert (2017) it is advisable to test nudges that are personalized according to the individual consumer. Personalization through algorithms that account for consumers' tastes, habits, and characteristics could prove highly effective as demonstrated by Von Zahn et al. (2023). Our moderation analysis has also shown that nudges only work above a certain level of environmental sensitivity and it is therefore conceivable, even desirable, to administer these nudges only to groups that are sensitive to the environment. Although this dissertation did not have the opportunity to explore further this perspective, it represents a significant opportunity for companies to enhance the impact of their nudging strategies.

6.3. Limitation and future research

This thesis provides an in-depth exploration of nudges to reduce product returns, but it is important to acknowledge several limitations.

Firstly, only two specific variants of nudges were tested, while many other potential nudge options remain unexplored. As explained above, other categories of nudges might prove effective in certain e-commerce contexts.

Furthermore, the survey was conducted based on a simulated purchase situation, limiting the measurement to the intention to return after this simulated transaction. A relevant next step would be to extend this research by testing these findings in real-world settings, where retailers implement the nudges, to determine whether this leads to an actual reduction in product return rates like in the Ghose et al. (2023) paper.

It should also be noted that the survey sample was relatively small, consisting of only 211 valid responses, which raises questions about its representativeness of e-commerce consumers as a whole. Additionally, the nudges were tested on a single type of product, specifically a white t-shirt. To better generalize the results, it would be beneficial to explore the effectiveness of these nudges on a variety of products, such as other types of clothing, electronic devices, and mass-market items, across different price ranges. This approach would allow for an assessment of whether the effectiveness of nudges is influenced by these differences in products and prices, leading to more robust recommendations for their application in e-commerce.

7. Conclusion

The aim of this dissertation is to test the effectiveness of two types of nudges in reducing online product returns. The problem of product returns is an important problem from an economic point of view for retailers and from an ecological point of view because of the significant greenhouse gas emissions they produce. The reasons for product returns are very diverse and this makes it difficult to find a single solution to reduce them.

Most ecommerce companies propose a very lenient return policy to encourage consumers to buy, but we can see that this kind of practice is being questioned by companies because the cost is so high. The scientific community has not reached a consensus on whether a lenient return policy is a better choice than a stricter one. In the absence of established truth, it is interesting to look for solutions to reduce returns that are not linked to the return policy, which is where nudges can be a useful option. These choice architecture design elements, based on the principles of bias and heuristics, have been used in a number of areas, particularly in online commerce. They have proved to be very effective, and there are different types available. While they have often been tested for ecological reasons, to encourage consumers to make more responsible choices (green nudges), they have hardly ever been tested for the specific purpose of reducing product returns. It therefore seemed important to expand the scientific literature by exploring the possibility of using these nudges to reduce consumers' willingness to return products.

To achieve this, we conducted a survey to test two types of nudge that were among the most common, most effective and easiest to implement in companies. Thanks to this survey and its 211 responses, we were able to establish that the use of an information nudge explaining that product returns had a significant environmental impact made it possible to decrease the willingness to return the product by 14% compared with the same situation without the nudge. The use of a social nudge explaining that more and more Belgians were giving up on returning their product for environmental reasons proved to be less effective, with a 6.3% reduction in the intention to return at a significance level of 5.3%. In an attempt to understand this further, we had to reject the hypothesis that the consumers' perception of environmental personal responsibility was a mediating variable between the presence of nudges and the reduction in the intention to return . We were also unable to fully prove that, as was the case in some studies about green nudges, environmental sensitivity of consumers have a moderating effect on the effectiveness of the two nudges tested. The figures obtained did not allow us to accept this hypothesis, but they did allow us to understand that nudges were effective only for people with a high environmental responsibility. To conclude, we can say that the use of information nudges to reduce e-commerce return rate is efficient but there is still a lot to discover how implementing nudges can help reduce product returns. The areas to be explored include other nudges and the personalisation of nudges to better target consumers.

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Abstract :

Online retailers are often faced with the problem of product returns. As well as being an environmental problem, these returns are very costly for companies, as most of them offer free returns. These lenient returns policies are increasingly being called into question, but there is no scientific consensus to prove the effectiveness of a stricter returns policy. Nudges could be a way of reducing the return rate without affecting the return policy. In this work, we test the use of two nudges whose messages are based on ecological incentives for this purpose. The first, an information nudge, proved effective in reducing the intention to return the product by 14%, while the second, a social norm nudge, was less effective, reducing return intention by 6%. We also found that these nudge are more effective with consumers with high environmental sensitivity and that perceived personal responsibility for sustainable consumption did not appear to be a mediating variable in the effectiveness of these nudges.

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