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Berlin School of Economics and Law

AI and Co. meeting the customer interface:

Sustainable fashion brands tackling the problem of e-commerce product returns

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AI	Artificial intelligence
AR	Augmented reality
CO_2	Carbon dioxide
CSRD	Corporate social responsibility directive
ESG	Environmental, social, governance
F	Test statistic
H	Hypothesis
M	Mean
ML	Machine learning
N	Total sample
p	p-value
P	Proposition
PPRM	Preventive product return management
RQ	Research question
SD	Standard deviation
Sig.	Significance level
t	t-value
VFR	Virtual fitting room
VR	Virtual reality
VTO	Virtual try-on

1 Introduction

1.1 Problem statement

Even in the aftermath of the pandemic, the world of e-commerce continues to thrive. Grand View Research (2022) revealed in their E-commerce Apparel Market Size, Share & Trends Analysis Report that the industry is projected to grow 9% by 2030 in comparison to data from 2022. Fashion products contribute a large part to this growth. For instance in Germany, only fashion products comprised 23% of e-commerce revenue in 2022 (Handelsverband Deutschland & IFH Köln, 2022).

As online orders continue to rise, the e-commerce industry faces a challenging task: increasing product returns. Generally, in the e-commerce industry, products bought online are returned at a rate three times higher than those bought in brick-and-mortar stores (Accenture, 2018). Among all product returns in the e-commerce industry, fashion products constitute 75% (Accenture, 2018). This is also underlined by the fact that every second fashion item ordered online will be returned (Stöcker et al., 2021).

These dimensions of product returns result in alarming consequences. The environmental impact caused by inefficient reverse logistics processes is significant. E-commerce fashion product returns contribute to 16 million metric tonnes of carbon dioxide (CO_2) emissions each year (Optoro, 2020). More importantly, many fashion brands choose cost-effective but unsustainable methods, disposing of product returns in landfills located in developing countries, leading to increased landfill waste and environmental hazards. E-commerce product returns generate 14% more landfill waste than traditional retail, with an estimated 2.6 million tonnes of fashion e-commerce product returns finding their way into landfills in 2020 alone (Optoro, 2020).

Product returns do not only harm the environment but also pose a financial challenge to fashion brands because return procedures are cost-intense. Moreover, they negatively impact profit margins and revenue losses (Heering & Rock, 2022). Additionally, an elevated rate of product returns can reduce customer satisfaction, brand loyalty and overall sales performance (Heering & Rock, 2022). Understanding the reasons for product returns becomes crucial, especially in the fashion industry, where multiple complex factors such as an incorrect fit, dissatisfaction with quality and subjective personal style preferences are widely spread as triggers for product returns among customers (Heering & Rock, 2022; Stöcker et al., 2021).

According to the Fashion on Climate Report 2020 by McKinsey & Company and Global Fashion Agenda (2020), reducing product returns could save up to 12 million tonnes of CO_2 emissions annually if the total of fashion product returns were reduced by 20%.

In search of more cost-efficient and sustainable solutions, emerging technologies may offer a glimmer of hope. Artificial intelligence (AI) holds the potential to revolutionize the way product returns are managed in the fashion industry. By surpassing traditional problem-solving techniques, AI offers intelligent automized solutions which go beyond human capabilities and may reduce product returns (Kreutzer & Sirrenberg, 2020). To name a few examples: Chatbots integrated into online shops are taking over the task of personalized communication performed by the salespeople in brick-and-mortar stores. Similarly, virtual fitting rooms (VFR) with human-like-looking avatars constitute the digital alternative to a physical fitting room (Cui et al., 2017; Welivita et al., 2017). These AI & Co.-based solutions promise to address consumer concerns, creating a more efficient and customer-centric approach to managing and preventing product returns in the e-commerce fashion industry.
This research delves into fashion e-commerce by exploring how AI and related technologies can prevent product returns and pave the way for decreased pollution caused by the fashion industry. Therefore, a specific focus is created on preventive product return management (PPRM), which aims to minimize the risk that product returns occur even before the customer places the order in the online shop. Thus, only solutions that can be implemented at the customer interface will be explored.

1.2 Objective of the research and research questions

This study aims to understand the current state of technical solutions based on AI & Co., which may help reduce product returns in fashion e-commerce. Thereby, the following research questions (RQ) arise:

> **RQ1:** *Can AI and Co. solutions be implemented at the customer interface to reduce product returns in e-commerce?*

> **RQ2:** *Which AI & Co. solutions that can be implemented at the customer interface are most likely approved to reduce product returns in e-commerce?*

This study will specifically investigate the role of interactivity in AI & Co. solutions that aim to reduce product returns in e-commerce as well as it will measure if either interactive or non-interactive AI & Co. solutions are more likely to reduce product returns. Since sustainability-unconscious consumers might have different claims when shopping online than sustainability-conscious consumers, RQ3 focuses on their perception of interactive and non-interactive solutions. Consequently, RQ3 was formulated:

> **RQ3:** *Is there a difference in the perception of interactive and non-interactive AI & Co. solutions between sustainability-conscious and sustainability-unconscious consumers?*

To the best of the author's knowledge, this is the first study to explore AI & Co.-based measures at the customer interface that aim to reduce product returns in fashion e-commerce while focusing on the effect of their interactivity.

This research is structured as follows: The first chapter defines the main terms of the empirical study. Thereupon, the reasons for product returns are examined. As this study focuses on PPRM, which aims to reduce the risk of returning the product before it was bought, the reasons for product returns are divided into those that occur before an order is placed and those that occur after an order is physically received. This selection aims to highlight those reasons that can be tackled in PPRM. Afterwards, measures addressing the letter product return reasons will be presented. For this purpose, it will be analyzed whether these measures proposed in the literature apply to the customer interface and can be supported by AI & Co. If this is the case, they qualify for further analysis and will be presented in greater detail by categorizing them into interactive and non-interactive solutions. Thereafter, the hypotheses (H) will be presented, which will be tested by conducting an experiment. The study's methodology and results are then presented by underlining the experiment's design and data analysis. Finally, the discussion section will consist of interpreting the results, drawing implications and highlighting limitations for practice.

2 Definitions

The following chapter provides an overview of the central terms and their definitions as well as it gives insides into the theoretical fundamentals for this research.

2.1 Sustainable fashion brands

This study aims to investigate the potential and role of AI & Co. technologies in reducing product returns with a specific focus on sustainable fashion brands. In this study, the term fashion brand refers to brands explicitly selling apparel online. This study does not explore the AI & Co. technologies' potential for products such as accessories, shoes, underwear, socks and luxury items.

Moreover, the focus is on sustainable fashion companies. The adjective "sustainable" refers to brands that actively seek to avoid product returns. However, it is not explicitly assumed that sustainable fashion brands explored in this study are directly perceived as CSR or slow fashion brands (Baumgarth & Binckebanck, 2015; Jung & Jin, 2014). Nevertheless, these brands can also find application in this study. Thereupon, this study refers to all sustainable fashion brands that fulfill the previously mentioned criteria.

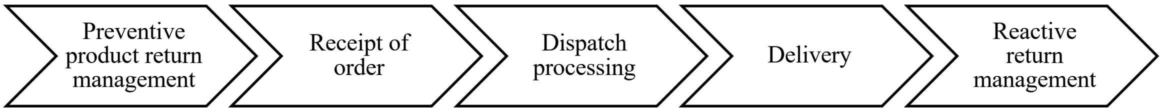
2.2 Return management

Product returns that arise from online orders are the focus of this research. Consequently, in the following chapters, return management describes the tasks that arise for online fashion retailers in the context of a product return and excludes product returns from purchases made in brick-and-mortar stores.

Return management includes all measures and activities related to the return process that occur from the company's side (Deges, 2017). Return management is required when a customer buys a product from an online shop, receives it and chooses to return it. This process involves various tasks, such as overseeing reverse logistics procedures and customer interactions. Additionally, managing and controlling multiple streams, including product, financial, and data streams, are essential to return management (Deges, 2017).

However, return management describes more than tasks that arise after the product is returned to the brand. Also, it includes measures to avoid returns prior to deciding on whether to keep or return the product after receiving it (Lämmermühle, 2016). These concepts are called preventive and reactive product return management. They are illustrated in figure 1 and will be explored in the following sections.

Figure 1 Return management process in e-commerce



Source: Own presentation based on Lämmermühle (2016) and Stahl et al. (2012)

2.2.1 Preventive product return management

PPRM seeks to avoid returns by taking action to reduce the chances of a customer wanting to return a product (Deges, 2017). Through consistently tracking and examining the reasons for product returns, companies can implement a process of ongoing improvement that results in a lasting decrease in return frequencies. Thus, preventing returns involves taking measures to eliminate the root causes of returns (Asdecker, 2023). As a result, PPRM focuses on a product's information and selection process by stimulating a conscious selection of products through assistance to influence the purchase decision (Deges, 2017).

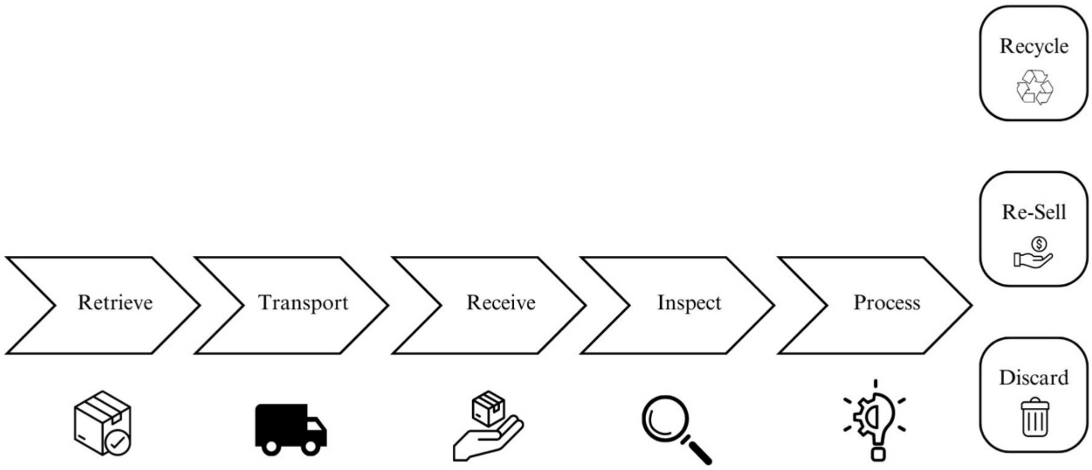
Furthermore, PPRM includes measures that aim to make the customer's decision of a product return more challenging. These measures could include both compensation and non-compensation options, such as receiving a coupon for the next order if the previous order was not returned or making the return process more time-consuming (Deges, 2017). Whereas a vast amount of literature focuses on the supply chain optimization processes of returns, PPRM, with its customer-focused approach, is a newer research field that leaves space for more profound insights (Stöcker et al., 2021; Walsh et al., 2014).

This research aims to investigate PPRM closely by investigating the reasons for product returns at the customer interface and tackling them by effectively preventing them. Consequently, measures with monetary compensation will be excluded from the research since they do not directly address the reasons for product returns. Nevertheless, reactive product return management will be explained in the following section to complete the definition of return management.

2.2.2 Reactive product return management

If the measures taken by PPRM are insufficient and thus, the customer is unsatisfied with the product after receiving it and wants to return it, it leads to reactive product return management (Deges, 2017). Reactive product return management involves processing unavoidable returns (Heering & Rock, 2022). This includes taking care of the reverse logistics process, including transport and labor costs, decision-making about the re-introduction into the sales cycle or disposal, as well as the payment of the customer's refund (Lämmermühle, 2016). The complexity in the optimization of this evaluation and processing procedure lies in the high proportion of manual work steps (Asdecker, 2014).

Figure 2 Product return process



Source: Own presentation based on Asdecker (2014)

It should be mentioned that the exact processing of returns varies from company to company (Asdecker, 2014). Nevertheless, identical processing steps can be identified (figure 2). The process begins with the delivery of the returned product by a logistics partner. After the brand receives the product, the return is inserted and processed in the internal information management system. Furthermore, employees process the information contained on the returns note. This includes, for example, the reasons for the return or any damages (Asdecker, 2014). The process ends with a decision on the further course of the product: ideally, the product is put back into the sales cycle. If this is not profitable enough for the companies for various reasons, the product is disposed of and is not resold. In addition, the recycling of the returned product is also an option at the end of the process. However, this is less frequently the case (Asdecker, 2014).

2.3 Customer interface in e-commerce

The study focuses on identifying technical solutions that can be used to minimize product returns by implementing these solutions at the customer interface. In e-commerce, the customer interface is the digital platform or user interface that allows customers to interact with an online business (Tucker, 2008). An e-business's website and mobile application are part of the customer interface. These digital areas that the consumer can access via the internet are also called front-end areas. The back-end, however, is where the internal data processing and analysis takes place. Thus, the back-end area is not accessible to the consumer but only to the e-business operator (Lämmermühle, 2016). The distinction between front-end and back-end is crucial, as a seamless user experience on the front-end, coupled with an integrated and efficient back-end strategy, can lead to customer loyalty and satisfaction (Roggeveen & Sethuraman, 2020).

2.4 AI & Co. technologies applied to reduce product returns

In this study, recent technologies based on AI & Co. are defined as tools and measures that:

(1) Utilize some form of engineering, analytics or digitization based on AI, machine learning (ML), virtual reality (VR) or augmented reality (AR), and
(2) Are linked to the reduction of product returns.

In the following, an explanation of ML and AI, as well as a definition VR and AR will be provided. As previously explained in chapter 1.2, the aim of this study is to investigate the differences between interactive and non-interactive AI & Co. measures in greater detail. Thus, the difference between interactive and non-interactive tools will be highlighted.

2.4.1 Artificial intelligence

The term "AI" has been popularized, particularly since the launch of ChatGPT by OpenAI in November 2022. However, as contemporary as the term seems to be, it originated in the 1950s. In 1956 a group of computer scientists and mathematicians organized a workshop called "Dartmouth Conference" during which they coined the term "AI" (Chintalapati & Pandey, 2022). However, the current capabilities of AI surpass the ideas of the scientists at the "Dartmouth Conference" workshop. Due to the numerous possibilities of applying AI and recent technical advancements, a radical development can be observed.

There are many definitions of AI in the literature and no clear boundaries for the term have been established yet (Dobrev, 2012; Heins, 2022; Kirkby et al., 2022; Siau & Yang, 2017). For this research, Kreutzer and Sirrenberg's (2020) definition of AI will be adopted:

"Artificial intelligence is the ability of a machine to perform cognitive tasks that we associate with the human mind. This includes possibilities for perception as well as the ability to argue, to learn independently and thus to find solutions to problems independently.".

Typically, AI-performance-levels can be classified into weak AI (or narrow AI), strong AI and superintelligence (Kirkby et al., 2022; Wang & Siau, 2019). Weak AI refers to the level of AI performance where it can carry out specific tasks based on the data it has been trained with by humans. This performance level is the current state of AI development. Moreover, strong AI refers to a level of performance where a machine can complete tasks at the same level as humans. This can include a variety of functions being performed simultaneously. Exceptional to these two performance levels of AI is "superintelligence". Here, the machine would surpass human intelligence (Kirkby et al., 2022; Wang & Siau, 2019).
When it comes to the functionality of AI, there are three types of analytic techniques: descriptive, predictive and prescriptive (Kreutzer & Sirrenberg, 2020; Roy et al., 2022).
As for the descriptive type of evaluation, data mining is utilized to gain insights into past events. In contrast, predictive analytic techniques describe future events based on statistical methodologies and forecasting. Finally, prescriptive analytics involves the utilization of algorithms to determine which actions should be taken to influence future events (Kreutzer & Sirrenberg, 2020; Roy et al., 2022).
Momentarily, there is no definitive boundary on AI's application fields, as different studies classify its uses differently., e.g. into ML, modeling, problem-solving or uncertain knowledge (Kreutzer & Sirrenberg, 2020; Russell & Norvig, 2012). Nevertheless, Kreutzer and Sirrenberg (2020) state that the most important AI application fields are natural language processing, natural image processing, expert systems and robotics.

Natural language processing refers to the capability of machines to capture, process and respond in a manner that resembles human communication. This could also include voice processing, such as speech-to-text solutions. Natural image processing refers to the process of creating, storing, and editing images, which also encompasses computer vision. In addition, expert systems can gather and analyze different types of information to generate guidelines for future actions. Lastly, robotics refers to the process of teaching a machine to carry out various tasks independently (Kreutzer & Sirrenberg, 2020).

2.4.2 Machine learning as an approach to artificial intelligence

In the following, an explanation of ML will be given. With its approach to AI, ML is focused on the creation of models and algorithms enabling computers to make predictions or decisions based on observed data sets (Baştanlar & Özuysal, 2014; Colliot, 2023). It involves detecting patterns and statistical relationships in data to avoid the provision of ongoing external instructions (Alpaydin, 2022).

Three types of learning are differentiated in ML: supervised learning, unsupervised learning, and reinforcement learning (Buxmann, 2019; Hahn & Scholz, 2020; Kersting et al., 2019).

Firstly, supervised learning trains algorithms with labeled data so that the algorithms learn to make decisions independently. Humans actively label data by explaining to the computer what information has been transmitted. For example, during a Google security check, users may be asked to select all image sections showing a car (the "labeling process"), which helps train the algorithm to recognize what cars look like (Buxmann, 2019).

Secondly, unsupervised learning uses algorithms to detect patterns in unlabeled data and to form groups out of such patterns by recognizing similar characteristics in large data pools (Colliot, 2023).

Finally, reinforcement learning involves implementing a reward or punishment system to determine the best course of action in a particular situation (Buxmann, 2019).

In other words, AI is a broad term used to describe the development of intelligent systems. Meanwhile, ML is a specific technique within AI that allows computers to learn from data and enhance their performance. There are also other approaches in AI research, such as neural networks or deep learning (Kreutzer & Sirrenberg, 2020). However, ML could play a particularly relevant role in product returns reduction due to its flexibility, scalability and ability to recognize complex patterns in large data pools.

2.4.3 Immersive technologies: Virtual reality and augmented reality

With the rapid development of AI and its approach to ML, virtual and augmented reality are becoming increasingly important in online shopping. For some customers, the physical lack of touch and try-out can present an obstacle in their online shopping experience. This lack can also trigger product returns. However, VR and AR may help bridge this gap and greatly

enhance the shopping experience by providing immersiveness (Cuomo et al., 2020; Jayaswal & Parida, 2023; Perannagari & Chakrabarti, 2020).
With the implementation of AR, users can add virtual objects like computer-generated images or texts to their surroundings (Perannagari & Chakrabarti, 2020). This feature lets customers view their environment in real-time with additional enhancements (Carmigniani & Furht, 2011). Crucial to the feature is access to a camera. Typically, a computer's webcam or specific glasses enable the user to fully enjoy the immersive AR experience. Since AR broadens the user's "real" reality, it also refers to the term mixed reality (Wohlgenannt et al., 2020).

Next to AR, VR describes an experience that goes beyond "real" reality. Available definitions of VR differ. However, for this research, VR will be defined as a "computer-generated digital environment that can be experienced and interacted with as if that environment was real" (Jerald, 2015). This definition has been chosen since it highlights the difference between VR and AR: VR is a newly created environment, whereas AR refers to an expansion of actual reality through computer-generated information. Extended reality is also spoken of when talking about VR and AR since extended reality includes all forms of real-and-virtually created surroundings (Wohlgenannt et al., 2020).
The two technologies VR and AR fall under the umbrella of immersive technologies (Suh & Prophet, 2018). Their experience (immersive experience) refers to an experience that blends the physical and virtual worlds, making virtual experiences more realistic (Soliman et al., 2017; Suh & Prophet, 2018).

2.4.4 Interactive vs. non-interactive solutions

This research will focus on the role of interactive and non-interactive technologies towards the reduction of product returns in fashion e-commerce at the customer interface. Therefore, interactive technologies require the customer's input and engagement to improve the online shopping experience by addressing specific reasons for product returns (Moriuchi et al., 2021). Therefore, the customer has to provide input at the front-end, such as personal data or enter a specific question. This input is then used by the AI & Co.-based measure to offer a customized solution addressing the customer's missing information when shopping online. An example of interactive technology in this context is a chatbot which require customers to ask appropriate questions to initiate a dialogue and offer personalized assistance.

To the best of the author's knowledge, there is no specific definition for non-interactive tools in the literature. Therefore, the definition is as follows: Non-interactive solutions based on AI & Co. operate without requiring any input or engagement from the customer. These solutions do not rely on additional data from the customer at the front-end when the customer visits the online store to make a purchase. The non-interactive solution approach is based on the analysis of pre-existing data collected from previous purchases and product returns in the online shop. This data analysis in the back-end aims to find patterns that enable the non-interactive solution to make recommendations on the front-end that support the customer in avoiding product returns. Consequently, the customer has the responsibility to evaluate whether this information influences their purchase decision. An example of non-interactive technology includes automated product description.

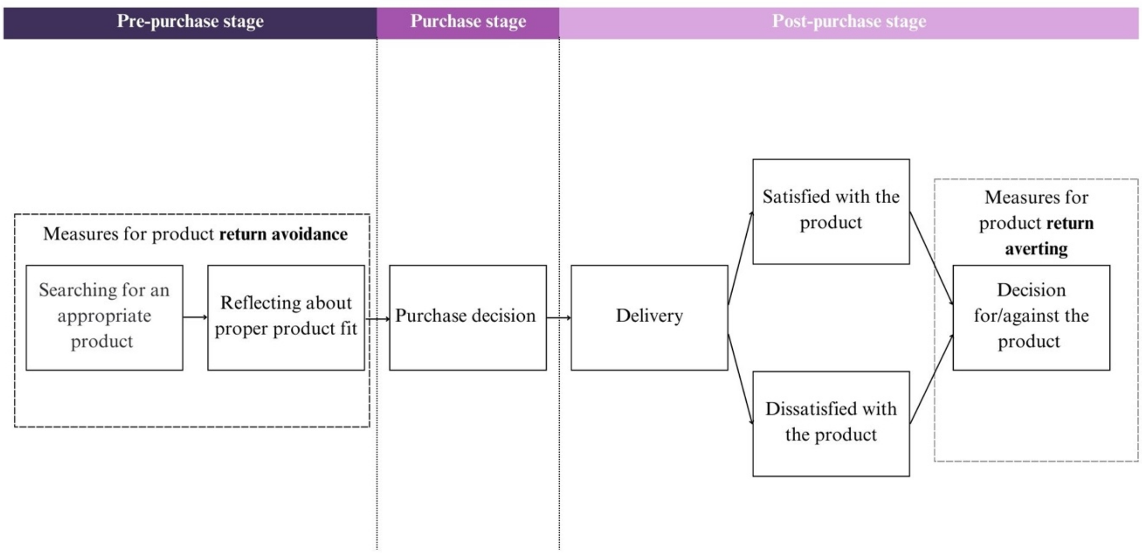
3 Product return reasons along the e-commerce purchase stages

After the definitory basis was clarified, it is crucial to understand a customer's purchase process and identify the specific stages where product returns can be prevented. Since some product return reasons cannot be addressed before the customer received the product, it is crucial to investigate those product return reasons that can be already addressed in the online shop. Thereby, this study will delve into the reasons for product returns, categorizing them by their drivers, as some reasons can occur due to the same triggers. By matching these drivers to the e-commerce purchase stages, the most common reasons for product returns that can be addressed before the customer places an order will be filtered. Consequently, the analysis will focus on the key drivers of product returns that occur at the pre-purchase stage and therefore play the most important role in PPRM.

3.1 Purchase stages in fashion e-commerce

As shown in figure 3, the process of shopping for fashion online is divided into three stages: the pre-purchase stage, the purchase stage and the post-purchase stage (Lemon & Verhoef, 2016; Stöcker et al., 2021). Moreover, there are two points at which the number of product returns can be measured: the product return avoidance point and the product return averting point (Stöcker et al., 2021).

Figure 3 Purchase stages with corresponding return prevention points



Source: Own presentation based on Stöcker et al. (2021)

Firstly, the pre-purchase stage includes the phase during which the customer searches for an appropriate product. After finding a product, the customer starts reflecting on the product's fit. During both steps of the pre-purchase stage, measures could be implemented to avoid product returns (Seo et al., 2016; Stöcker et al., 2021). It should be noted that searching for a suitable product on touchpoints other than the brand's website or application, such as social media, is excluded from this study as the focus is on the customer interface.
Secondly, the purchase stage describes the customer's decision to purchase. At this stage, the customer places the product in their basket, proceeds to checkout, pays for the product and enters any necessary data (Burke, 2002; Roggeveen & Sethuraman, 2020). Once the decision to purchase the product has been made, return prevention cannot occur until the product has been delivered (Stöcker et al., 2021).

Finally, the post-purchase stage includes the delivery of the product. Once the customer receives the product, they unpack it and assess whether it meets their expectations (Zhou et al., 2018). However, even if the product meets their expectations, it is not guaranteed that they will keep it. Reasons for such returns include the customer's inability to afford the product financially as well as not needing it anymore (Saarijärvi et al., 2017). In this stage, measures can be implemented that might influence the decision to keep the product at the product return averting point. Such measures could be gifting a coupon for every kept delivery or informing the customer about their return impact while displaying their own return behavior (Deges, 2017; Stöcker et al., 2021).

This study aims to find the best ways to avoid product returns at the customer interface alongside the usage of AI & Co. technologies pre-purchase. Therefore, the upcoming sections will discuss measures that can be implemented at the return avoidance point and the customer interface.

3.2 Empirical studies on product return reasons

Since this study focuses on the customers' perspective, it is vital to analyze the reasons for product returns from their perspective. Product returns in fashion e-commerce have various and intricate origins. Mainly due to the product's uncertain fit and the lack of touch and feel of the apparel's texture, fashion retailers have a particularly challenging task at hand to transmit these pieces of information to their customers virtually (Stöcker et al., 2021).

In the review process, both qualitative and quantitative studies were analyzed. As a result, it has become clear that the reasons for returns are numerous and complex.

It was evident that the qualitative study delved deeper into the reasons for product returns, while the quantitative studies did not explore all the reasons covered in qualitative research. In order to provide a better understanding of the reasons for product returns, qualitative research results will be explained first. The investigator of this study has classified the reasons discovered through qualitative research to simplify the comparison of quantitative studies and match the product return reasons to the pre- or post-purchase stages where they could potentially be tackled.

In the following, the results of the interviews conducted by Saarijärvi et al. (2017) will be presented. Furthermore, the surveys conducted by ibi research (2017), Stöcker et al. (2021) and Leong et al. (2023) will be analyzed. These observed studies are listed according to their empirical design and location of investigation in table 1.

Table 1 Empirical studies on product return reasons

Author(s) (year)	**Title**	**Empirical design**	**Location**
Saarijärvi et al. (2017)	Uncovering consumers' returning behaviour: a study of fashion e-commerce	Qualitative; Interviews; N=21	Multi-national
ibi research (2017)	Trends und Innovationen beim Versand – Was erwartet der Kunde?	Quantitative; Online survey; N=1.007	German
Stöcker et al. (2021)	New insights in online fashion retail returns from a customers' perspective and their dynamics	Quantitative; Online survey; N=8.396	German
Leong et al. (2023)	Solving fashion's product returns How to keep value in a closed-loop system	Quantitative; Online survey; N=1.503	UK

Source: Own presentation based on ibi research (2017), Leong et al. (2023), Saarijärvi et al. (2017) and Stöcker et al. (2021)

Before presenting the results of Saarijärvi et al.'s (2017) qualitative study, it is important to emphasize that several researchers such as Pristl and Mann (2021), Stöcker et al. (2021) or Deges (2017) attempted to categorize the reasons for product returns in order to search for solutions that could tackle the problem of product returns. For instance, Pristl & Mann

(2021) differentiate in their research between objective and subjective reasons (Pristl & Mann, 2021). According to them, objective reasons are not influenced by individual opinions. They include defects or mistakes in the delivery or ordering process and price developments (e.g. the product is on sale after the purchase and during the return timeframe). In contrast, subjective reasons are individually influenced by the customer. Their motives and evaluation post-product-delivery influence the decision of whether the product will be kept or returned (Pristl & Mann, 2021).

Other studies categorized the product return reasons differently: Deges (2017) and Stöcker et al. (2021) distinguish between the product information gap, reasons that occurred due to consumer behavior as well as price and fulfillment/service (Deges, 2017; Stöcker et al., 2021). The study conducted by Saarijärvi et al. (2017) proposes different categories also.

This study is a valuable source as it provides an in-depth analysis of various factors that trigger online fashion returns. The researchers conducted 21 semi-structured interviews with individuals who have bought fashion items online and made at least four purchases in the past 12 months (Saarijärvi et al., 2017).

Saarijärvi et al. (2017) clustered the statements of the interview participants into groups according to similar drivers for product returns to identify managerial implications for each driver group, namely: "Reclamation driven, "Order fulfillment driven", "Competition driven", "Disconfirmation driven", "Size chart driven", "Feeling driven", "Money shortage driven", "Faded need driven", "Benefit maximization driven" and "Just trying out driven" (Saarijärvi et al., 2017). Also, they gave an explanation for each driver.

However, the goal of Saarijärvi et al.'s (2017) study was not to match these drivers for product returns to the purchase stages and their return prevention points. Thus, the author of this study adapted the categories for product return drivers by Saarijärvi et al. (2017) and proposes the following categories: Fulfillment driven, sizing driven, defects driven, misleading product display driven, misleading product information driven, personal style driven, changing needs driven, cost/budget driven, planned return driven and wrong order driven. The following example will underline why this new classification of product return drivers is necessary: Saarijärvi et al. (2017) put into their driver group "disconfirmation driven" the statements "A different hue than expected", "The material differs from what was expected", "Misleading product description" and "Misleading product pictures". However, based on the definition of AI & Co. technologies in section 2.4, it might be the case that one AI & Co.-based technology could be used to address the problem of the product's visual presentation and another one could address the problem of the product description. Thus, the statements are differentiated into the new driver groups “Misleading product description” and “Misleading product display”.

Table 2 Product return reasons categorized by their drivers

Category of product return driver[1]	**Reasons for product returns**[2]	**Explanation**[1]
Fulfillment driven	>Delivery of the wrong product >Delayed delivery[3]	Returns resulting from issues related to logistics and fulfillment
Sizing driven	>Different fit than expected >Different fit perceived by the customer >Ordered multiple sizes of the product with the intention to keep one product in the right size	Returns resulting from sizing issues
Defects driven	>Product has defects	Returns resulting from products that have defects
Product display driven	>Misleading product pictures >Hue differs from what was expected	Returns resulting from discrepancies between the product images and the physical product
Product description driven	>Misleading product description >The material differs from what was expected	Returns resulting from discrepancies between the product description and the physical product
Personal style driven	>Customer does not like the product’s style >Product feels wrong >Ordered multiple colors of the same product with the intention to keep one product with the best color >Ordered multiple products for the same occasion with the intention to keep one product	Returns resulting from the product not aligning with the customer’s personal style or preferences
Changing needs driven	>Faded need of the product >Impulsive purchase	Returns resulting from a change in the customer’s needs or preferences post-delivery
Cost / Budget driven	>Pre-defined budget breached >Regrets on spending a lot of money	Returns resulting from budget constraints
Planned return driven	>Product ordered to try it on for fun (showrooming) >Occasional piece	Returns resulting from purchases that were planned to return pre-purchase
Wrong order driven[3]	>Unnoticed mistake during ordering process. Placed order seemed to be right. After delivery, the mistake has been noticed[3]	Returns resulting from unnoticed mistakes during the purchase process

[1]Adapted from Saarijärvi et al. (2017).

[2]Based on Saarijärvi et al. (2017).

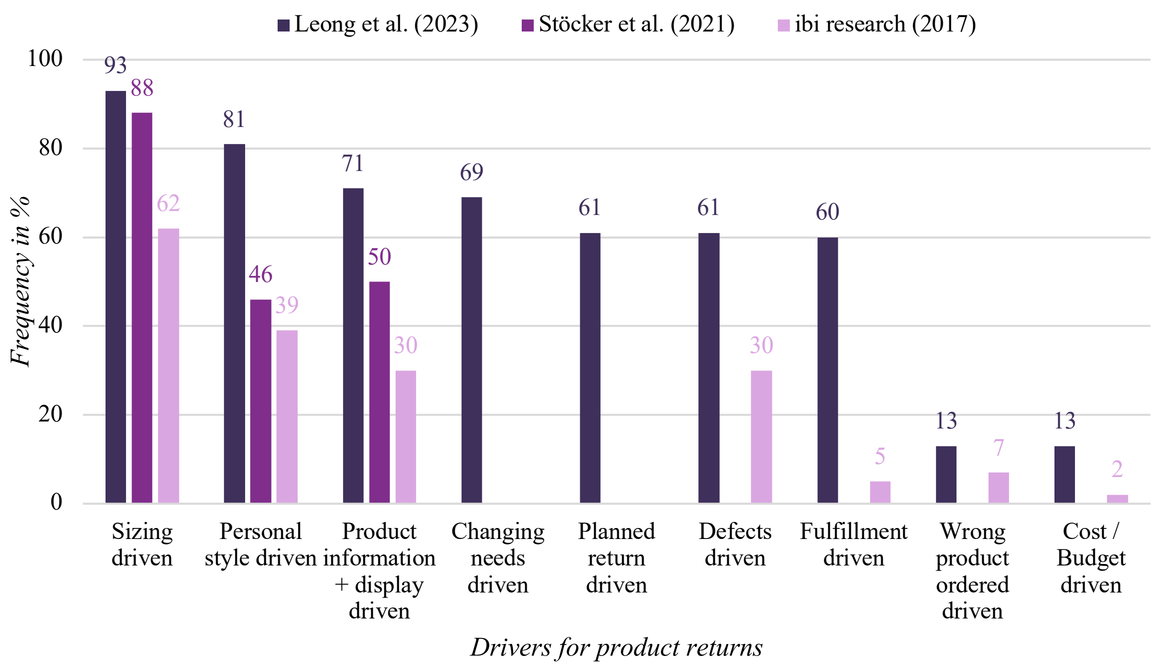
[3]Based on Leong et al. (2023); ibi research (2017).

Source: Own presentation based on Saarijärvi et al. (2017)

Moreover, the researcher extended the overview of reasons for product returns since additional reasons for product returns were found in other literature. The overview of the statements from the interviews, the additional product return reasons as well as the product return drivers that will be used for further analysis can be observed in table 2.

In figure 4, the three quantitative studies conducted by Leong et al. (2023), Stöcker et al. (2021) and ibi research (2017) are compared to gain insights into the distribution and the common occurrences of the product return drivers. All surveys allowed the participants to give multiple answers. Additionally, it has to be said that none of the surveys give detailed insights into demographic differences when looking at the reasons for product returns. Moreover, in figure 4 it can be observed that Leong et al.'s (2023) survey provides the most detailed insights into the drivers for product returns. Thus, the results of this survey will be presented in more detail.

Figure 4 Empirical studies' results on drivers for product returns



Source: Own presentation based on ibi research (2017), Leong et al. (2023) and Stöcker et al. (2021)

Leong et al. (2023) conducted an online study with a sample of 1.503 respondents from the UK, including participants of all genders and age groups ranging from 14 to over 75 years old (Leong et al., 2023). Out of all the participants, 52% were female, 47% were male, and 1% identified as another gender or non-binary. Regarding age groups, 47% were born between 1997-2012 (Gen Z), 19% were born between 1981-1996 (Millennials), and 34% were born after 1981 (Leong et al., 2023). This survey specifically targets the UK market, yet it provides valuable insights into the various reasons for product returns, which is why it was chosen for analysis.

It is striking that the size of the product was reported as the most common reason for product returns. This is mainly due to the lack of sizing standardization and the uncertainty in determining one's own body measurements, which leads to the procurement of the product in the wrong size (Deges, 2017). In the UK-focused survey, 93% of the participants stated that sizing is often a reason for their returns (Leong et al., 2023).

Two out of three surveys underline that the second most frequent reason for product returns is based on the customer's style preferences. This could include, e.g., ordering the product in different colors because they are unsure which color would suit them best or simply because they do not like the item because it does not suit their style. Especially the field study conducted by Leong et al. (2023) exposed that 81% of the participants experienced uncertainty regarding their style after receiving an order (Leong et al., 2023).

Additionally, embellished or inauthentic product photos can raise expectations of the product, leading to disappointment upon delivery (Deges, 2017). Furthermore, if product descriptions lack detail, it can lead to varying product expectations. As a result, misleading product descriptions and visualizations are in the third place of the most common product return reasons as 71% of the UK-focused sample stated that their product returns originate in the latter drivers (Leong et al., 2023). These three drivers of product returns are the ones that were conducted by all the observed surveys. Additionally, product defects were declared by 61% as a reason for product returns by Leong et al.'s field study (Leong et al., 2023). They may be caused due to different factors, such as insufficient finishing in the manufacturing process or damage caused during delivery.

Apart from the UK-focused study, the other surveys have rarely investigated the other drivers for product returns such as changing needs driven returns, planned returns, fulfillment driven returns, cost/budget driven returns and wrong order driven returns.

In summary, reasons for product returns are highly multifaceted. However, most studies underline that the dominant reasons for product returns are rooted in sizing and personal style issues as well as misleading product information and visualization.

3.3 Product return reasons according to the purchase stages

As announced at the beginning of section 3, this chapter aims to reveal the drivers for product returns according to the purchase stages and identify which drivers are the most frequently stated ones at the purchase stages. Subsequently, the drivers for product returns are matched either to the pre-purchase stage (at the product return avoidance point) or the post-purchase stage (at the product return averting point).

3.3.1 Product return reasons according to the pre-purchase stage

In table 3, the categories of product return drivers have been matched to the purchase stage. The first drivers indicate those that arise at the pre-purchase stage and could potentially be tackled at the customer interface. Insecurity about the correct size and fit arise already at the pre-purchase stage.

Table 3 Categories of product return drivers according to the pre-purchase stage

Category of product return driver[1]	**Explanation**[1]	**Frequency**[2]	**Purchase stage**[3]
Sizing driven	Returns resulting from sizing issues	93%	Pre-purchase stage
Personal style driven	Returns resulting from the product not aligning with the customer's personal style or preferences	81%	Pre-purchase stage
Product display driven	Returns resulting from discrepancies between the product images and the physical product	71%	Pre-purchase stage
Product description driven	Returns resulting from discrepancies between the product description and the physical product	71%	Pre-purchase stage
Planned return driven	Returns resulting from purchases that were planned to return pre-purchase	61%	Pre-purchase stage

[1]Adapted from Saarijärvi et al. (2017).

[2]Based on Leong et al. (2023).

[3]Investigators own classification based on Stöcker et al. (2021).

Source: Own presentation based on Leong et al. (2023) and Saarijärvi et al. (2017)

The customer's reflections on whether the product matches their personal style are also undertaken pre-purchase (Stöcker et al., 2021). Both product visualization and product description influence the customer's expectations and since both are integrated into the customer interface, these categories are also assigned to the pre-purchase stage.

Finally, planned returns have also been assigned to the pre-purchase stage, as the consumer's intention to return a product after wearing it once, as well as not wanting to keep the product in the first place, may already be evident at the pre-purchase stage.

3.3.2 Product return reasons according to the post-purchase stage

The reasons that occur post-purchase are listed in table 4. These reasons include e.g. instances where a customer no longer needs the product after receiving it or where a customer realizes they do not want it after an impulsive purchase.

Table 4 Categories of product return drivers according to the post-purchase stage

Category of product return driver[1]	**Explanation**[1]	**Frequency**[2]	**Purchase stage**[3]
Changing needs driven	Returns resulting from a change in the customer's needs or preferences post-delivery	69%	Post-purchase stage
Defects driven	Returns resulting from products that have defects	61%	Post-purchase stage
Fulfillment driven	Returns resulting from issues related to logistics and fulfillment	60%	Post-purchase stage
Cost / Budget driven	Returns resulting from budget constraints	13%	Post-purchase stage
Wrong order driven[4]	Returns resulting from unnoticed mistakes during the purchase process[4]	13%	Post-purchase stage

[1]Adapted from Saarijärvi et al. (2017).

[2]Based on Leong et al. (2023).

[3]Investigators own classification based on Stöcker et al. (2021).

[4]Based on ibi research (2017).

Source: Own presentation based on Leong et al. (2023) and Saarijärvi et al. (2017)

Defective products which lack proper finishing or underwent logistical issues can also cause returns. It is important to note that these drivers are not always apparent post-purchase. In cases where supply chain issues, e.g. shortages in the warehouse, are known to the retailer ahead of the customer's purchase, those triggers already appear consequently pre-purchase. Thus, this specific case should then be assigned to the pre-purchase stage. If a customer feels regretful about overspending post-delivery, this is equally considered part of the post-purchase stage (Stöcker et al., 2021). Finally, if the customer orders the wrong product and realizes it after receiving it at home, this is also considered part of the post-purchase stage, as it cannot be anticipated beforehand.

As a result, the main drivers for product returns that could be tackled at the customer interface during the pre-purchase stage have been indicated. Additionally, they are the most frequently named drivers for product returns compared to those at the post-purchase stage.

In the following sections, it will be analyzed which AI & Co.-based solutions can be implemented at the pre-purchase stage to tackle these drivers.

4 Tackling the problem of product returns at the pre-purchase stage

Next, empirical studies will be presented that have explored ways to decrease product returns. A specific focus on tools that can be implemented at the customer interface and are based on AI & Co. will be created. Furthermore, the solutions will be categorized into interactive or non-interactive solutions and elaborated upon by focusing on the driver for product returns that they address.

4.1 Empirical studies on measures to reduce product returns

In the following, solutions to prevent product returns will be presented. First of all, it is essential to highlight that there are some studies that examine the perspective of retailers on valuable tools and measures to reduce product returns (Bergmann et al., 2013; bevh, 2023). For example, a study conducted by the EHI retail institute in 2021 explicitly had a retailer focus. In this study, 108 German, Austrian and Swiss retailers participated in a survey and gave insights into their experience with product returns. However, this survey was not explicitly focused on the fashion industry. Nevertheless, the retailers stated that the essential measures to reduce product returns are detailed product information (83%) and the possibility of contact in the form of a chat (48%) (Bergmann et al., 2013). In addition to previous studies that analyzed retailers' perspectives, the study conducted by Stöcker et al. (2021), specifically gives an overview of measures to reduce product returns at the different purchase stages. The study also presents measures that can be explicitly integrated into the customer interface. Moreover, Stöcker et al. (2021) differentiate the interactivity of these proposed measures. However, interactivity as a variable is not further investigated in their study (Stöcker et al., 2021).

In table 5, the proposed measures that can be implemented at the customer interface are presented. The author of this study has extended said table by measures that have not yet been listed by Stöcker et al. (2021) but are further mentioned in the literature in the context of product return reduction. Furthermore, the author of this study examined the applicability of AI & Co. technologies necessary for the realization of each measure. It is important to note that existing AI & Co. solutions can be applied to several listed measures in the table. Therefore, the table does not explicitly differentiate between AI & Co.-based solutions for each proposed measure. Instead, it focuses on presenting the proposed measures and their potential applicability through AI & Co.-based solutions.

Table 5 Measures to reduce product returns at the customer interface

Proposed measure[1]	Practical example(s)[1]	Literature[1]	AI & Co. solution[2]	
Virtual fitting of articles Visualizing the item to see how the product could look on oneself	Mister Spex, Otto	Deges (2017); Walsh et al. (2014)	**Virtual try-on**	**Interactive solution[2]**
Find out individual size Using an interactive online tool to find out one's size	Kohl's, Mytheresa	Deges (2017); Heinemann (2022)	**Virtual try-on**	
Size advice—figure types Comparing figure types to see which one is most similar to oneself	About You, Sizeable, The Yes	Deges (2017); Heinemann (2022)	**Virtual try-on**	
Assisted shopping Real-time guidance from the vendor to assist in choosing size, color and product	John Lewis, BAUR	Heinemann (2022)	**Chatbot**	
Size recommendation—previous purchases Vendor is providing size recommendations based on customers' past purchases and returns	Zalando	Deges (2017); Heinemann (2022)	**Size recommendation**	**Non-interactive solutions[2]**
Informative product description[3] Precise and complete product description	Shopify; MyTheresa[3]	Harreis et al. (2022); Dopson (2021)[3]	**Automated product description**	
Product recommendations[4] Personal product recommendations based on previous purchases and browsing	About You, Zalando, Otto[4]	Heinemann (2022); Berman (2023)[4]	**Product recommendation**	
Information model size Information on model's size who wears the product	Asos, Nelly, Target, Pretty Little Thing, River Island	Deges (2017); Heinemann (2022)	-	**Non-applicable solutions[2]**
Favorite article for comparison Size comparison of a new item with the size of a favorite item	Next (Bra Size), Thirdlove	Deges (2017); Heinemann (2022)	-	

[1]Based on Stöcker et al. (2021).

[2]Investigators own classification based on Stöcker et al. (2021).

[3]Based on Harreis et al. (2022); Dopson (2021).

[4]Based on Heinemann (2022); Berman (2023).

Source: Own presentation based on Stöcker et al. (2021)

As a result, two interactive solutions stand out: the use of a chatbot allows the customer to experience assisted shopping, as well as the implementation of a virtual try-on (VTO) technology for sizing and try-on the product online. In addition, size recommendations in text form based on ML data analysis could help the customer to choose the right size and automated product descriptions would help to ensure accurate and informative product descriptions. In the literature, product recommendations have also been presented in the context of reducing product returns, thus completing the non-interactive AI & Co. solutions (Berman, 2023).

Nevertheless, the measure "Information model size" was classified as not applicable, as the implementation of AI & Co. technologies would not necessarily simplify the process of the measure, because the size of the model wearing the product has to be entered manually into the fashion brand's retail system. However, automating the implementation of this information in the product description simplifies the process, especially for larger brands that offer a multitude of products in their online stores. Furthermore, the measure "Favorite article for comparison" has also been proposed by Stöcker et al. (2021). However, only underwear brands are mentioned as practical examples. As underwear is explicitly excluded from this study, the measure "Favorite article for comparison" was consequently categorized as not applicable due to the variety of fashion item cuts.

4.2 Interactive solutions based on AI & Co.

Section 4.1 discussed various solutions for tackling product returns. The next section will focus on AI & Co.-powered solutions that can be seamlessly integrated into the customer interface.

4.2.1 Virtual try-on

The two interactive solutions which actively engage customers will be highlighted: VTO tools and chatbots. These solutions require customer participation to generate further results (Moriuchi et al., 2021). As a first interactive solution, VTO tools are discussed. These are immersive technologies that allow the user to try on the fashion item and experience online how the product would look on them (Zhang et al., 2019). VTO technologies can provide extra features that use ML, such as a mix-and-match function or product recommendations (Lee et al., 2022). Furthermore, these technologies can be used not only in online shopping but also in in-store shopping (Lee et al., 2022). There is a lot of theoretical discussion about immersive VTO technologies (Dizdarevic, 2022). However, many forms of VTO solutions are still in the first stages of development (Lee et al., 2022).

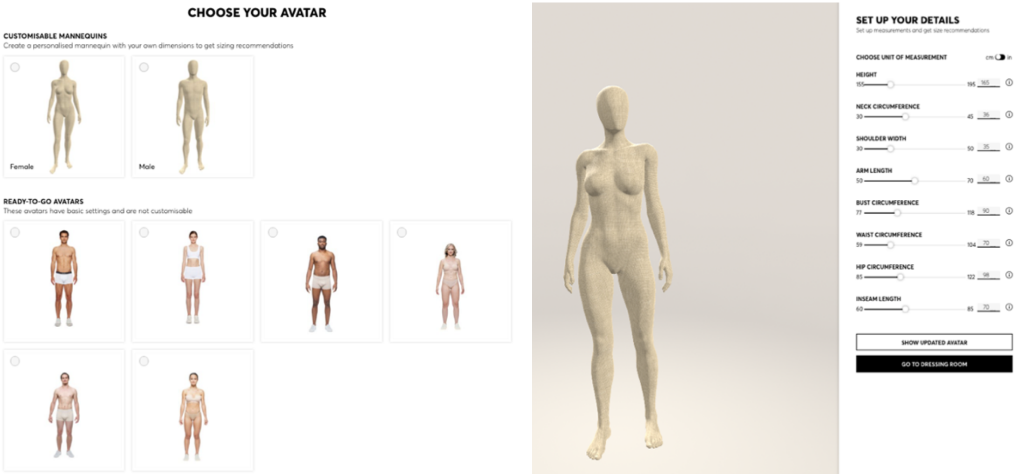
Different visualization forms of VTO technologies exist: on the one hand VR- or AI-based VFRs enable the user to experience how the product would look on them completely virtually. On the other hand, AR-based VTO solutions let the user experience through a camera how certain items would look on them (Merle et al., 2012; Mohammadi & Kalhor, 2021).

VFRs that are based on 3D visualization enable the customer to see how the product would fit based on an avatar or a mannequin (Lee et al., 2022). Generally, VFRs have different approaches to how they rebuild the body of the customer. This can be done by uploading photos of the own body, by manually entering the body measurements or by body scanning (Lee et al., 2022; Lee & Xu, 2020; Merle et al., 2012). In order to give a practical example, the Hugo Boss VFR and its functionalities will be described in detail. This example has been chosen since it is currently achievable and usable within existing VR-features. Hence, other VFR solutions, such as VFRs that involve avatars based on customer pictures, do not function smoothly enough yet. Moreover, it has to be mentioned that VFRs are not always based on VR but can also be AI-based (Vue, 2023).

The German company Hugo Boos offers premium clothing, accessories and fragrances for women, men and kids (Hielscher, 2021). The brand cooperates with the VTO solution provider Reactive Reality (Reactive Reality, 2023b). In August 2022, Hugo Boss introduced its first VFR in cooperation with Reactive Reality which is available for all customers in Germany, France and the UK (Hughes, 2022). Reactive Reality was founded in 2014 in Graz and specializes in virtual fashion (Reactive Reality, 2023a). Its virtual fitting platform PICTOFIT enables Hugo Boss' customers to experience the VFR (Morletto, 2022).

There are four steps that the customer has to follow to interact with the VFR:
First, after entering the VFR, there are two options: Either the customer chooses a pre-made avatar that resembles their body type. These avatars look like humans but are standardized. This means that the body measurements as well as hair and skin color are unchangeable. Or the customer creates their personalized mannequin by entering their individual body measurements, which can be observed in figure 5. Thereby, the mannequin takes on one's figure, yet personalized faces, skin or hair colors cannot be set (Hugo Boss, 2023).

Figure 5 Step 1 of the Hugo Boss VFR



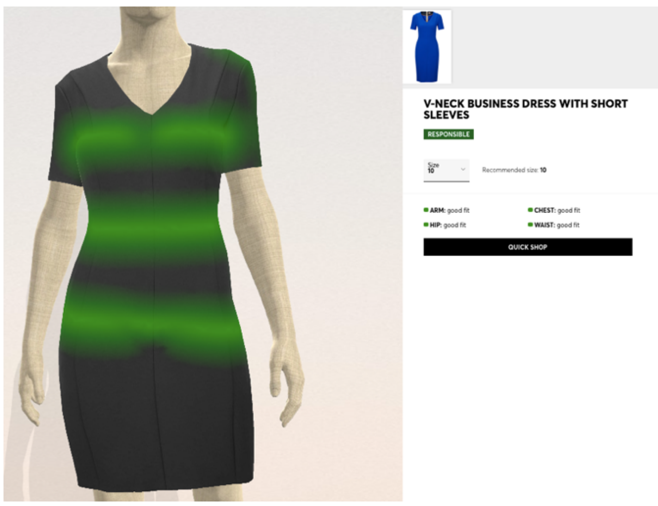
Source: Hugo Boss (2023)

Secondly, the VFR feature allows a 360-degree view of the garment on the selected avatar to see how the product would look on oneself. If the customer has selected other items for the fitting, they can be combined to create a cohesive outfit.

Thirdly, the VFR features a "fit check" call-to action-button that gives the customer the most suitable size after clicking it. It additionally offers information about the product's fit by using colors to indicate areas of the body where the product may fit and where it might not fit right (see figure 6).

Finally, after trying on the product virtually, the customer can complete the purchase and check out (Hugo Boss, 2023).

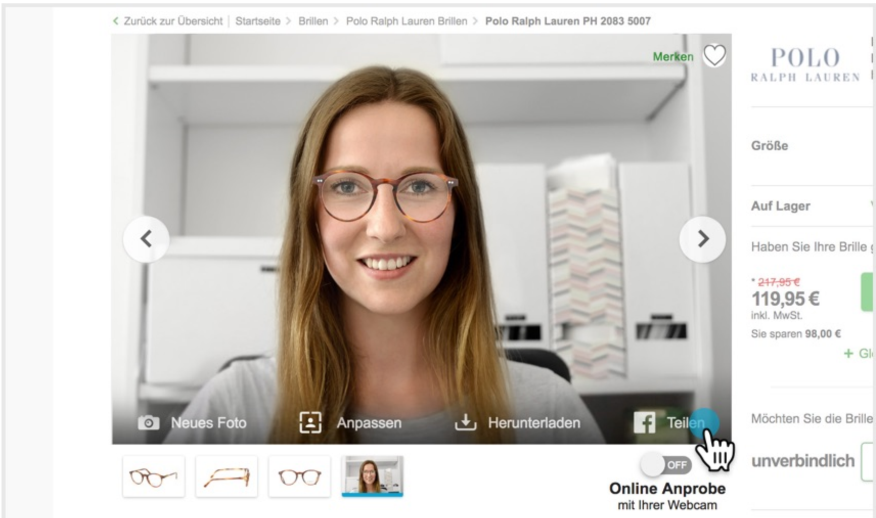
Figure 6 Step 3 of the Hugo Boss VFR



Source: Hugo Boss (2023)

Next to the VFR, AR-based solutions offer customers the possibility to experience a product on themselves through a technical device, e.g. a laptop equipped with a camera, through which AR features are implemented. AR is a widely spread feature in the fashion world, particularly in a social media context. On Instagram, Snapchat or TikTok users are offered filters to try on make-up or accessories (Jayaswal & Parida, 2023). Fashion retailers have also embraced such features in their e-commerce channels to assist customers in making informed purchasing decisions. The implementation of AR features works well, particularly in the accessories and make-up sector. Mister Spex, Germany's largest online optician, for instance, offers its customers to try on their glasses virtually (Mister Spex, 2023a). Their AR-based VTO solution can be observed in figure 7.

Figure 7 Mister Spex VTO



Source: Mister Spex (2023b)

Although AR-based VTO features have been accessible for a considerable period of time, fashion brands have been hesitant to implement them due to concerns about simulation accuracy and consequently about potentially dissatisfied customers with improper fitting results post-purchase (Jayaswal & Parida, 2023; Lee & Xu, 2020). Especially in the apparel context retailers state that the functionality requires improvement as some customer-owned devices lack the technical capabilities to provide accurate body scans for product fittings.

In summary, VTO solutions may effectively bridge the gap between online and offline shopping, by allowing customers to virtually try on products and see how they would look in real life. Especially VFRs have been pointed out as potential measures to reduce product returns in fashion e-commerce. These solutions tackle multiple reasons for product returns at the pre-purchase stage such as those that are sizing driven, personal style driven and misleading product display driven. However, if the virtual fitting technology is complicated and time-consuming, online shoppers may decide to dismiss it while purchasing (Zhang et al., 2019). In that case, it would miss the goal of reducing the risk of product returns.

4.2.2 Chatbot

Chatbots have emerged as a transformative technology in e-commerce, offering significant potential for enhancing customer experience and customer satisfaction (Chen et al., 2021). With their conversational capabilities powered by AI and natural language processing, chatbots can engage customers in personalized interactions, providing real-time assistance and guidance throughout the purchasing journey (Ashfaq et al., 2020). Furthermore, chatbots can enable a personalized shopping experience by quickly and accurately answering customer questions and henceforth addressing customer needs. By implementing a chatbot, companies operating in online retail are able to improve their customer service efficiently (Cui et al., 2017).

Chatbots have been present in online retail for a considerable amount of time. However, in spring 2023, Zalando, the leading German fashion and lifestyle platform in Europe, made a substantial contribution to the fashion industry by announcing the launch of a chatbot powered by OpenAI (Mc Gowran, 2023). According to Zalando, their assistant will provide customers with product information and recommend items based on their preferences and needs. The assistant should additionally consider the customer's previous orders to create a personalized shopping experience (Zalando, 2023). However, at the moment, the chatbot has not been released to the public. Only a limited group of customers can access the beta version (Mc Gowran, 2023; Zalando, 2023).

As a result, chatbots could contribute to reducing product returns by tackling the reasons driven through misleading product information and style issues.

4.3 Non-interactive solutions based on AI & Co.

In section 4.1 non-interactive solutions such as automated product descriptions and size recommendations were distinguished. In theory product recommendations have been discussed as well. Yet, it should be discussed critically whether they actually aim to decrease the number of returned products, as recommendations usually increase the likelihood of impulse purchases as discussed further below.

4.3.1 Automated product description

AI-based natural language processing techniques and ML algorithms enable retailers to let the generative AI write product descriptions and improve the customer experience (Harreis et al., 2022). The text is created by using data from existing product descriptions that serve as examples for the desired outcome of the company's product description (Harwardt & Köhler, 2023). The use of AI is particularly exciting for product descriptions, which often challenge retailers due to the large number of products that they sell (Kirkby et al., 2022). AI can write these product descriptions in the branding style, taking into account the text's completeness, comprehensibility and consistency (Scheier & Held, 2019). In order to minimize product returns, it is recommended by Shopify to always include in a product description the fit of the product, the materials processed in the product and the returns policy (costs and timeframe) (Dopson, 2021).

To give an example of the capabilities and the human-likeliness of an AI-generated product description, the following Gucci AI-generated product description for the MyTheresa website has been translated from German to English:
"Give your shoe collection a new distinctive elegance with designer shoes from Gucci. With their high-quality materials, such as feather-light suede, or sophisticated prints, such as the pineapple-patterned jacquard, Gucci's signature shoes are the perfect companion for any occasion. Indulge in lambskin-trimmed Princetown loafers or extravagant leather pumps. Store the label's signature Horsebit loafers or on-trend high-top sneakers." (AX Semantics, 2021).

In summary, automated product descriptions could potentially address those product returns that are driven by inaccurate or incomplete product descriptions. This can be achieved by providing correct and comprehensive information while also aligning the text with the company's brand language.

4.3.2 Size recommendation

The lack of standardized sizing in the fashion industry leads to uncertainty about how well a product will fit customers (Leong et al., 2023). In section 3.2, it has already been investigated that this is the main driver for product returns across all observed studies. Size recommendations based on ML algorithms have the potential to become a valuable tool for fashion e-commerce brands to effectively guide the customer towards choosing the right size

(Lasserre et al., 2020; Sheikh et al., 2019). These recommendation systems work in three phases, using deep learning algorithms: The first phase is the information collection phase. During this phase, data about the customer's previous orders are collected. Additional data is considered in the form of sizing feedback from other customers who have previously returned the product, e.g. because it was too small. Afterwards, during the learning phase, patterns based on the collected data are calculated. Thereupon, during the recommendation phase, the analysis output is recommended to the customer (Chakraborty et al., 2021). This output is usually directly shown at the front-end on the product website in proxy to size selection options and could be for instance saying: “The product fits too small – we recommend getting one size larger.”.

Notably, size recommendations that actively require the customer's body measurement input also exist (Guigourès et al., 2018). However, these recommendations are categorized as interactive solutions since the recommendation for those systems requires active input by the customer in addition to data collection and analysis in the back-end.

For the purpose of this study, the non-interactive version of size recommendations will be investigated further in section 5. Consequently, implementing non-interactive size recommendations might potentially tackle the problem of size and fit, which might help decrease the potential for product returns.

4.3.3 Product recommendation as a critically examined solution

An additional approach to decreasing product returns, as discussed in the literature, is through product recommendations (Berman, 2023; Henkel, 2020; Stöcker et al., 2021). The German-based tech-company trbo is specialized in personalizing and optimizing the shopping experience of companies such as erlich textile, L’Oréal or Triumph (trbo, 2023). One of their solution’s features is to analyze the customer’s browsing and purchasing behavior. Out of said data, trbo extracts recommendations for products that the customer has not yet considered through the utilization of AI and ML algorithms (Roggeveen & Sethuraman, 2020). Trbo's CEO, Felix Schirl, believes that personalized product recommendations in fashion e-commerce can decrease the likelihood of product returns (Henkel, 2020).

As the ML and AI algorithms’ goal is to learn about the customer’s personal preferences, product recommendations might minimize reasons for product returns driven by personal style complaints.

However, as product recommendations also encourage the customer to make additional purchases, it is questionable whether said technology does in fact reduce product returns or whether it even encourages the customer to make additional (impulse) purchases which could in turn increase rather than decrease returns.
Therefore, it remains to be seen whether product recommendations actually help to minimize returns. Nevertheless, it is clear that this type of personalized shopping experience contributes to improved customer satisfaction (Heinemann, 2022).

The previous section revealed AI & Co. solutions that can be implemented at the customer interface to reduce product returns in fashion e-commerce. Moreover, a differentiation between the solutions' interactivity was made: As interactive solutions, VTO solutions and chatbots have transpired. It was also underlined that these interactive solutions address multiple drivers for product returns. As non-interactive solutions, automated product descriptions, size recommendations and product recommendations have developed. Nevertheless, each non-interactive solution addresses only one driver for product returns. However, no AI & Co. solution was found to tackle planned returns. It also follows that no AI & Co. solution has been found that simultaneously addresses all the drivers for product returns.

Table 6 summarizes these interactive and non-interactive solutions and the drivers for product returns that they address at the customer interface during the pre-purchase phase.

Table 6 AI & Co. solutions and their solution approaches to product return drivers

	Interactive solutions		**Non-interactive solutions**		
Drivers for product returns	Virtual try-on	Chatbot	Automated product description	Size recom-mendation	Product recom-mendation
Sizing driven	x			x	
Personal style driven	x	x			x
Product display driven	x	x			
Product description driven			x		
Planned return driven					

Source: Own presentation

4.4 Hypotheses

Based on the research objectives and the current state of the literature, four hypotheses are proposed.

Overall, it can be expected that the use of AI & Co. technologies can potentially reduce the risk for product returns through its efficient capability of processing and analyzing data while matching it to the customer's preferences (Leong et al., 2023). Therefore, H_1 was formulated:

> **H_1:** *Implementing AI & Co. solutions at the customer interface reduces the likelihood of product returns.*

In section 4, a differentiation of interactivity has been formulated in order to categorize the AI & Co. tools that address the drivers for product returns at the pre-purchase stage. Because non-interactive tools do not require any interaction or engagement by the customer, it is to be expected that the implementation of non-interactive solutions supports the customer in ordering products that they will not return post-purchase. As a result, H_2 was developed:

> **H_2:** *Non-interactive AI & Co. solutions reduce the likelihood of product returns.*

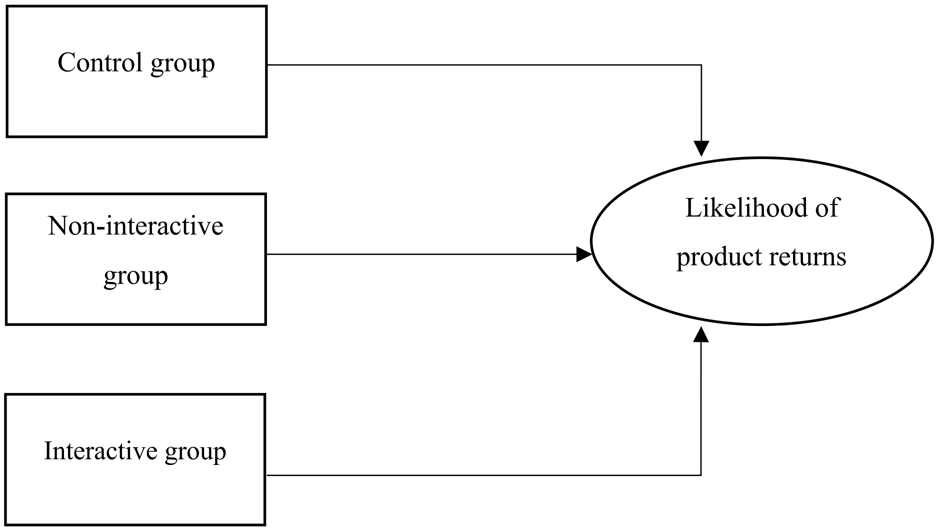
Since interactive tools require the customer's participation, a certain risk arises that the customer will not use the interactive tool during the buying process. However, if the customer decides to engage with the interactive tool, it can be assumed that this will reduce product returns. Therefore, H_3 has been formulated:

> **H_3:** *Interactive AI & Co. solutions reduce the likelihood of product returns.*

Finally, H_4 describes the degree of product return reduction. In section 4, it has been discovered that interactive tools address more drivers for product returns compared to non-interactive solutions. Therefore, it is assumed that interactive solutions minimize the potential for product returns more than non-interactive tools. For this specific argument, H_4 has been formulated:

> **H_4:** *Interactive AI & Co. solutions reduce the likelihood of product returns more than non-interactive AI & Co. solutions.*

Figure 8 Independent variables and dependent variable of investigation



Source: Own presentation

In the upcoming sections of this study, the hypotheses above will be examined and tested in an experiment in order to gain a better understanding of how AI & Co. solutions affect product returns and to what capacity interactivity plays a role in the process. Figure 8 illustrates the independent variables "control group", "non-interactive group" and "interactive group" that will be examined for the dependent variable "likelihood of product returns" in the following chapter.

5 Methodology and results

The methodology and results of the conducted study will be explained in order to elaborate on whether AI & Co. solutions can reduce product returns. For this purpose, the study design is elaborated on, followed by the data collection process and the resulting sample. Then, the study's results are presented.

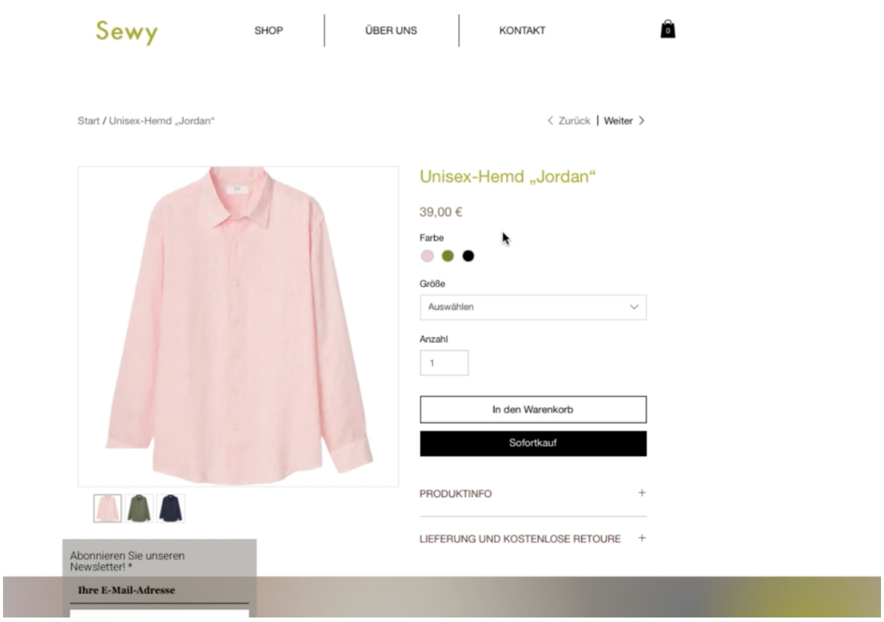
5.1 Design

In order to test both the effect of AI & Co. tools which could potentially reduce product returns and the effectiveness of interactivity, an online experiment was chosen as the research design. Considering that not all the interactive and non-interactive tools identified in section 4 could be tested in one experiment, it was decided to test one tool representing each solution category: interactive and non-interactive. Since most product returns are driven by sizing issues, it was decided to select an interactive and non-interactive solution which addresses this driver. Therefore, VFR was chosen as the representative interactive tool and size recommendation as the representative non-interactive tool.

The design was integrated into the survey tool Unipark in order to conduct the online experiment (Unipark, 2023). The sample was divided into three experimental groups. Each group received a stimulus in the form of a video showing the case chosen for the experiment: the (fictive) fashion online shop *Sewy.* The stimuli showed the online shop's website which was created using the website development tool Wix (Wix, 2023). Each experimental group was shown the product website of a unisex shirt available in *Sewy*'s shop. The shirt was available in rosé, olive and black to ensure that most of the participants would find a color of the shirt that matches their taste. The shirt was available in standard sizes: XS, S, M, L and XL. Additionally, the price for the shirt (39€), as well as a product description that contained information about the shirt's fabric (linen), the care instructions and the location of the production site (Italy) was displayed. Moreover, a tab concerning the return policy was shown.

The control group saw the website as it just had been explained without any further implemented tool that might help the customer in avoiding a product return (figure 9). The other experimental groups saw the same video but slightly manipulated.

Figure 9 Video screenshot of the stimulus for the control group

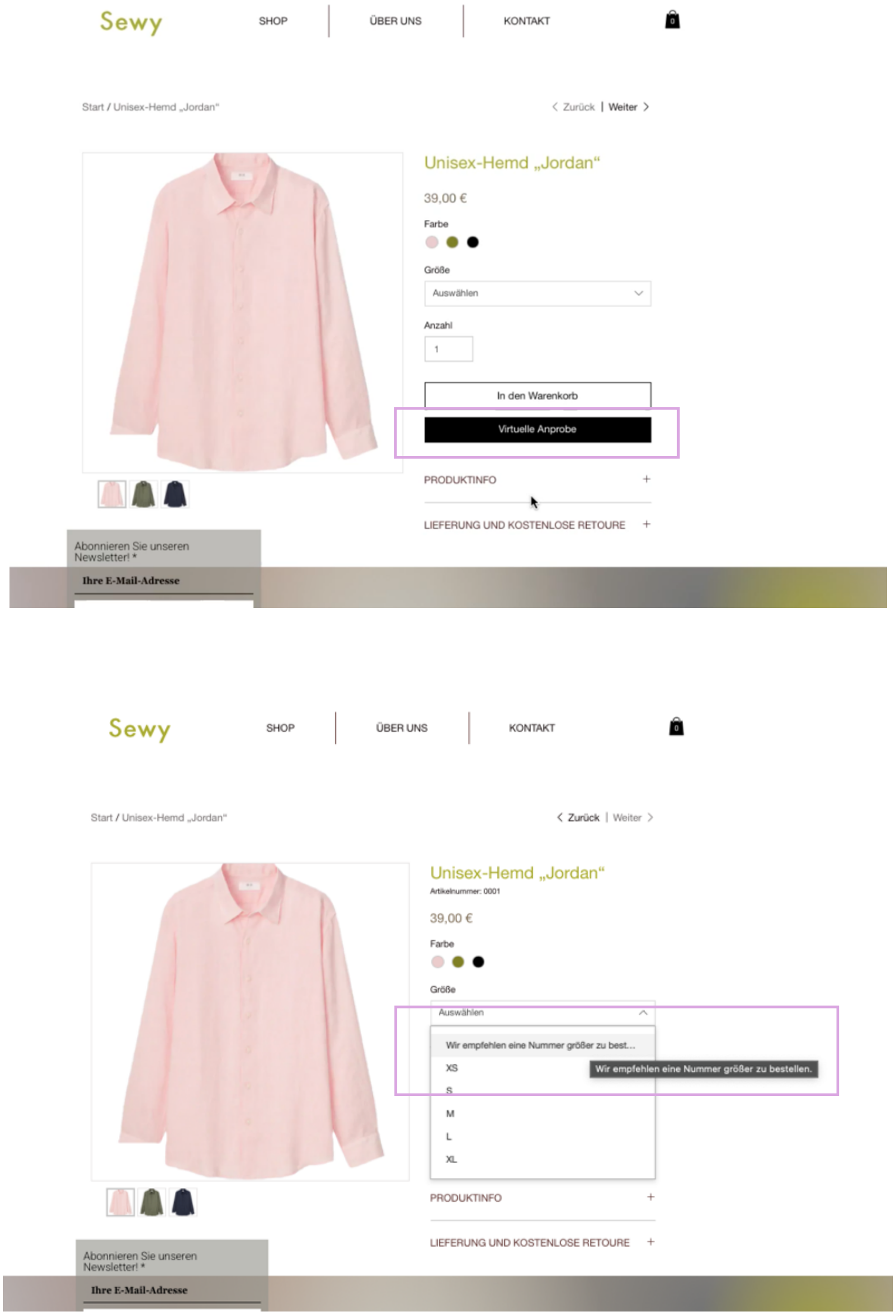


Source: Own presentation

The second group was selected to test the effect of the interactive solution VFR. As illustrated in figure 10, they saw the exact video of *Sewy*'s product website with an additional call-to-action button spelling out “virtual fitting”. Since VFRs are not widespread in e-commerce yet, the functionality of the VFR example from Hugo Boss, that has been elaborated on in section 4.2.1, was briefly explained (Hugo Boss, 2023). It should be noted, however, that the experimental group that tested the interactive VFR solution was not able to interact with the VFR, since it only received a manual explaining how the VFR would work.

The third group was selected to test the effect of non-interactive tools. As a result, this group was shown the same product website as the control group. Additionally, their website provided information about the product's fit in the form of a size recommendation. The product description and size selection indicated that the product runs small. Therefore, it is recommended to choose a size larger than usual (see figure 10).

Figure 10 Video screenshot of the stimuli for the interactive and non-interactive group



Source: Own presentation

Above the three stimuli have been clarified. In the following, the structure of the online experiment's design will be introduced. It is important to note that in the first part of the experiment, all groups were given the same questions. Thereupon, each group was shown their group-specific stimulus and was then asked questions related to their particular case.

The first part of the experiment which was identical for all participants is divided into six sections. At the beginning of the study, the investigator welcomed the participants and informed them briefly about the subject of the study and the guidelines for data protection.
In the second part, the participants were asked demographic questions concerning gender, job, income, residence, age and birth month (items 1-6) in nominal scales. The investigator has chosen the last demographic question (birth month) to categorize the participants into the three groups described above. The control group includes those born from January to April, the interactive group includes those born from May to August and the non-interactive group includes those born from September to December.
The third part focuses on the participants' buying behavior during online shopping. Thus, item 7 investigates the importance of sustainability when online shopping. This is achieved by adopting a 5-point Likert scale (1=very important, 5=very unimportant). Item 8 examines the frequency of the participant's online shopping by measuring it on a nominal scale divided into months.
Fourthly, a definition of the term "returns" is provided in order to ensure comparability between the results of the following items which involve said term: "This survey often talks about "returns". This only includes returns that have occurred when buying new clothing items from online shops. This includes all garments EXCEPT underwear, socks, luxury items, accessories and shoes." (translated from German to English).
In the fifth section, the participants' return behavior is investigated. Item 9 explores the frequency of product returns. Whereas item 10 investigates the willingness to avoid product returns by the participant and item 11 actively discovers the knowledge about the effect of product returns that the participant might have. All three items are based on nominal scales.
In the final part which was the same for all participants, there is a matrix consisting of a five-point semantic differential scale. This matrix aims to understand the reasons why participants return products. Based on the analysis of reasons for product returns from chapter 3, each item represents one driver for product returns. Due to the number of separate reasons for product returns stated in chapter 3, the investigator decided not to ask about all of the reasons in the survey in order to avoid an increased drop-out rate (Saarijärvi et al., 2017).

Afterwards, the differentiation into three groups is made by presenting each group its group-specific stimulus. Once each stimulus of the online shop *Sewy* was shown to each group, all three groups were asked to elaborate on how many articles they would order on a nominal scale. Additionally, it was enquired how they would estimate the likelihood of returning the

product on a 5-point Likert scale (1=very likely, 5=very unlikely). The interactive and non-interactive groups were additionally asked if they came across a VFR or size recommendation on a nominal scale before and whether they would consider buying the size recommendation of their appropriate tool (5-point Likert scale going from 1=very likely, 5=very unlikely). Moreover, the interactive group was asked to state if they would consider using the VFR at all and if not, whether they would be open to stating their reasons for avoiding it.
Finally, the investigator expressed gratitude for the participation and provided an email address for comments.

Since this research follows a quantitative design, it is ensured that the quality criteria for quantitative research designs are met. These criteria consist of validity, reliability and objectivity (Hussy et al., 2013). The research design has been designed with the aim of investigating the research objective for this study. Therefore, validity is met. In addition, comparable statistical data is collected during the online experiment, which guarantees reliability. Finally, this study is objective because the test conditions and test results are independent of each other and the analysis was conducted without consulting third parties who have conducted similar studies or are currently conducting similar studies (Hussy et al., 2013).

Ahead of the actual field study, a pretest was conducted to test whether the target group would correctly understand the experiment and to ensure no ambiguities would arise. The pretest was carried out by a total of 18 participants (6 participants in the control group, 6 participants in the interactive group and 6 participants in the non-interactive group). 10 participants identified as female and 8 participants identified as male. Moreover, 12 participants are students and 6 participants are employees. The pretest revealed that one fundamental reason for product returns was missing in the item concerning these reasons. Since the exact reason "The product arrived too late" was mentioned by 3 participants, it was added to the item. Additionally, some remarks were made concerning the improvement of a general overview by adding bold font for keywords. These remarks were gratefully acknowledged and transferred. Luckily, there were neither comprehension errors nor problems with the perception of the stimuli in terms of readability and visibility. Thus, the experiment was ready to launch.

5.2 Data collection and sample

The data collection period was extended from June 15 to June 25, 2023. The survey was distributed via social media accounts on Instagram, WhatsApp and LinkedIn. In addition, the investigator recruited participants in a university library in Berlin by handing out the QR code of the online experiment. The online experiment was further shared by family members, work colleagues, fellow students and acquaintances. Hence, the sample is random as participants of random samples are either part of the researcher's social environment or related to them (Raab et al., 2018).

Due to the researcher's age and social environment, this method of participant recruitment is likely to attract many Gen Z and Millennial students as well as young adults. In addition, it will likely result in participants with predominantly lower incomes. Therefore, it can be assumed that this sample cannot represent the entire (German) population. Nevertheless, this study is relevant because it provides early insights into the perception and effect of interactivity when using AI & Co. solutions to reduce product returns in fashion e-commerce.

The total sample (N) of the experiment is N_{Total_Sample}=151. To ensure the accuracy and relevance of the results, questionnaires completed by respondents who shop online less frequently than once every six months were discarded. In addition, questionnaires completed by respondents who stated that they would never return after their online fashion purchase were also eliminated.

As a result, the total size of the sample used for further analysis is $N_{Total\_Sample\_Cleaned}$=112. In the following, the socio-demographics are analyzed for $N_{Total\_Sample\_Cleaned}$=112. Of all the participants who are part of the cleaned sample, 70% identify as female, 29% identify as male and 1% identify as non-binary. In addition, 60% are Gen Z, 27% are Millennials, 12% are Gen X and only 1% are Baby Boomers. It is also worth noting that 48% of the sample are students, confirming the assumption that students and Gen Z will dominate the sample. The second largest group in the sample are employees, making up 39% of the sample. Homemakers, freelancers, unemployed and other professionals comprise the rest of the sample. These distributions also reflect the average income of the sample, which is between 1.000€-2.000€.

As already explained in 5.1, the experimental groups were randomly divided into three groups according to their month of birth: the control group (received no integrated AI & Co. stimulus), the interactive group (received the VFR stimulus) and the non-interactive group

(received the size recommendation stimulus). This results in the following sample group sizes: $N_{Control}$=36, $N_{Interactive}$=39 and $N_{Non\text{-}interactive}$=31. It should also be noted that 6 participants in the interactive group indicated that they were not willing to use the VFR. Thus, 39 participants agreed to use the VFR ($N_{Interactive}$=39). The other 6 participants who would not do so will be explored in more detail in further descriptive findings later.
Table 7 shows the socio-demographic insights, including gender and age for each experimental group ($N_{Control}$=36, $N_{Interactive}$=39 and $N_{Non\text{-}interactive}$=31) in percent.

Table 7 Socio-demographic descriptive evaluation by groups in % ($N_{Control}$=36, $N_{Interactive}$=39, $N_{Non\text{-}interactive}$=31)

		Control	Interactive	Non-interactive
Gender	Female	56	75	80
	Male	41	25	20
	Diverse	3	0	0
Age	18-26 years	75	51	58
	27-43 years	0	9	13
	44-58 years	20	22	16
	59-77 years	5	18	10
	+78 years	0	0	3

Source: Own presentation

5.3 Data analysis and results

In the following, the results of the conducted online experiment will be analyzed. Therefore, a descriptive evaluation will give an overview of the reasons for product returns according to the sample ($N_{Total\_Sample\_Cleaned}$=112) as well as insights into the respondents' return behavior. Moreover, the hypotheses will be tested using an independent samples t-test with a significance level of 5%. Additionally, further descriptive insights will be provided based on the online experiment's results.

5.3.1 Descriptive evaluation of product return behavior and product return reasons

Table 8 shows the reasons for product returns investigated in the survey with the corresponding means (M) and standard deviations (SD). It is noticeable that, as described in section 3.3, the most popular reason for product returns reported by the sample ($N_{Total\_Sample\_Cleaned}$=112) is sizing driven ("The product did not fit (was either too small or too large)." (M=1.48; SD=.816), followed by a personal style driven reason ("I did not like the product.”) (M=2.37; SD=1.273). Thirdly, the participants indicated that their expectations regarding the quality of the product were not met, which is most likely a reason for returning a product due to the product description and/or product display (M=2.72; SD=1.330).

Table 8 Descriptive evaluation of product return reasons ($N_{Total\_Sample\_Cleaned}$=112)

5-point Likert Scale: 1=Does apply often; 5=Does not apply often

	M	SD
The product did not fit (was either too small or too large).	1,48	,816
I did not like the product.	2,37	1,273
The product did not meet my quality expectations.	2,72	1,330
I ordered the same product in different sizes or colors with the intention of keeping only one variation of the product.	2,79	1,525
The product description or product display in the online store was not true to reality.	2,87	1,417
The product was delivered defective.	3,66	1,418
A different product than what I ordered was delivered.	4,08	1,343
I regretted spending too much money.	4,09	1,227
Buying the product was a spontaneous impulse. I did not need the product at all.	4,12	1,228
I accidentally ordered the wrong product or size/color of product.	4,17	1,192
The product arrived too late.	4,40	1,086
I wore the product once and then returned it.	4,96	,247

Source: Own presentation

Further descriptive analysis revealed that there is no relationship between gender and the frequency of online shopping. The same result appeared for the relationship between gender and the frequency of returning products (see Appendix). In addition, further descriptive insights found that there is a relationship between participants who are concerned about sustainability during online shopping and their awareness of what happens to returned products since they seem to be informed about it (see Appendix).

5.3.2 Hypotheses evaluation

The following section tests the hypothesis formulated in section 4.4 based on the results of the online experiment. An independent t-test was performed to test the hypotheses. In general, the hypotheses can be supported if the significance level $p < 0.05$ results from the independent t-test.

Table 9 gives a descriptive overview of the experiment's results by group measuring the likelihood of returning the product from the *Sewy* online shop after each experimental group ($N_{Control}=36$, $N_{Interactive}=39$ and $N_{Non\text{-}interactive}=31$) had seen their respective stimuli.

Table 9 Descriptive evaluation of product return likelihood ($N_{Control}=36$, $N_{Interactive}=39$, $N_{Non\text{-}interactive}=31$)

5-point Likert Scale: 1=very likely to return; 5=very unlikely to return

	Group	N	M	SD
ProdRetLikeli	Control	36	2,50	1,230
	Interactive	39	3,51	,894
	Non-interactive	31	3,10	,907

Source: Own presentation

To test the first hypothesis H_1: *Implementing AI & Co. solutions at the customer interface reduces the likelihood of product returns,* an independent t-test is performed to measure the effect of AI & Co. solutions without precision on their interactivity. In table 10, the item's data of the interactive and non-interactive groups ($N_{Non\text{-}interactive}+N_{Interactive}=70$) are compared with the control group ($N_{Control}=36$). The Levene's Test indicates that equal variances cannot be assumed between these groups as F=7.417 and Sig.=.008. Thus, a Welch test is performed and shows that the likelihood of a product return is significantly reduced when an AI & Co. solution ($N_{Non\text{-}interactive+Interactive}=70$) is used compared to the control group ($N_{Control}=36$) that has not implemented an AI & Co. solution ($t(54.1)=-3.65$; $p<.001$). Therefore, H_1 can be supported.

Table 10 Independent samples t-test for H_1 ($N_{Control}$=36, $N_{Non\text{-}interactive}$+$N_{Interactive}$=70)

		Levene's Test for Equality of Variances		t-test for Equality of Means					
						Significance			
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
ProdRetLikeli	Equal variances assumed	7,417	,008	-4,051	110	<,001	<,001	-,842	,207
	Equal variances not assumed			**-3,653**	**54,100**	**<,001**	<,001	-,842	,230

Source: Own presentation

Looking more closely at the role of interactivity, the second hypothesis H_2: *Non-interactive AI & Co. solutions reduce the likelihood of product returns,* is tested.
In table 11, again the equality of variances is not assumed (F=4.854; Sig.=.031).

Table 11 Independent samples t-test for H_2 ($N_{Control}$=36, $N_{Non\text{-}interactive}$=31)

		Levene's Test for Equality of Variances		t-test for Equality of Means					
						Significance			
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
ProdRetLikeli	Equal variances assumed	4,854	,031	-2,228	65	,015	,029	-,596	,267
	Equal variances not assumed			**-2,278**	**63,583**	**,013**	,026	-,596	,261

Source: Own presentation

The Welch test underlines that there is a significant reduction in the likelihood of product returns ($t(63.58)=-2.278$; $p=.013$) generated by non-interactive solutions ($N_{Non\text{-}interactive}=31$) compared to the control group ($N_{Control}=36$). Consequently, H_2 is also supported.

Next, the effect of implementing interactive solutions at the customer interface is tested for H_3: *Interactive AI & Co. solutions reduce the likelihood of product returns.*
Table 12 again shows that H_3 is supported, because interactive solutions significantly reduce the likelihood of product returns when used by the customer ($t(62.05)=-4.133$; $p <.001$) as equal variances are also not to be assumed ($F=6.565$; Sig.=.012).

Table 12 Independent samples t-test for H_3 ($N_{Control}=36$, $N_{Interactive}=39$)

		Levene's Test for Equality of Variances		t-test for Equality of Means					
						Significance			
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
ProdRetLikeli	Equal variances assumed	6,565	,012	-4,278	79	<,001	<,001	-1,011	,236
	Equal variances not assumed			**-4,133**	**62,051**	**<,001**	<,001	-1,011	,244

Source: Own presentation

Finally, H_4 suggests that *interactive AI & Co. solutions reduce the likelihood of product returns more than non-interactive AI & Co. solutions.* Table 13 shows that the Levene's Test did not reveal any evidence for unequal variances between the groups ($F=.011$; Sig.=.916). As a result, equal variances can be assumed. The independent t-test showed that interactive solutions reduce the probability of product returns significantly more than non-interactive solutions ($t(74)=-1.972$; $p=.026$).

Table 13 Independent samples t-test for H_4 ($N_{Interactive}$=39, $N_{Non\text{-}interactive}$=31)

		Levene's Test for Equality of Variances		t-test for Equality of Means					
						Significance			
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference
ProdRetLikeli	Equal variances assumed	,011	,916	**-1,972**	**74**	**,026**	,052	-,414	,210
	Equal variances not assumed			-1,967	64,059	,027	,054	-,414	,211

Source: Own presentation

Based on these results, it can be concluded that all hypotheses are supported. Implementing either a non-interactive or an interactive solution significantly reduces the likelihood of product returns. However, the interactivity of the AI & Co. solutions plays a role in their effectiveness because interactive solutions reduce the likelihood of product returns significantly more than non-interactive solutions.

5.3.3 Further descriptive insights

The supported hypotheses showed that interactive AI & Co. solutions reduce the likelihood of product returns more than non-interactive solutions. To clarify, as mentioned earlier, 39 participants expressed their intention to use the interactive VFR ($N_{Interactive}$=39). However, the interactive group actually consists of 45 participants. The remaining 6 participants stated that they would not use the VFR in the online shop *Sewy* ($N_{Interactive\_Refused}$=6). These participants were asked within an open question to explain why they would refuse to use the VFR. The reasons stated were that a VFR is both too time-consuming and too complicated for the user, mainly because a VFR requires the user to plan ahead as measuring their body parts in advance is necessary. They also stated that they believe the results of a VFR would be too inaccurate, e.g. the fabric's fall characteristics are unrealistically simulated, therefore, a VFR would be of no benefit to them. Another concern expressed by a participant concerned their preference to wear baggier clothes - how would the VFR or the online shop *Sewy* know about their personal style preference? Finally, one participant said that it would be beneficial to VFR's acceptance if the avatar actually represented their own body including hair and skin color as well as their face, rather than just their measurements on a featureless mannequin (as explained in section 4.2.1 and the experiment, the Hugo Boss VFR can show the accurate body measurements only by adopting them in form of a mannequin).

When exploring the perceptions of interactive and non-interactive solutions, differences in perceptions regarding the relevance of sustainability to the consumer when buying fashion were found.

Table 14 shows that within the sustainability-unconscious group, the control group had a high probability of returning the product from the online shop *Sewy* (M=2.64; SD=1.093). There was almost an equal likelihood in both the interactive (M=3.32; SD=.994) and the non-interactive group (M=3.29; SD=.994) concerning product returns. Hence, no difference in product return likelihood between the two presented technologies could be found. When asked about their willingness to order the recommended size by the VFR (M=1.77; SD=.842) or one size larger by the size recommendation (M=2.03; SD=1.016), participants in both groups did not report any relevant difference in their purchase decisions based on the recommendations.

In contrast, the sustainability-conscious group exhibited different patterns. Sustainability-conscious participants revealed a difference in their perception of interactive vs. non-interactive solutions: The control group was highly likely to return the product from the online shop *Sewy* (M=2.29; SD=1.437). The interactive solution reduced the likelihood of returning the product (M=3.70; SD=1.020) compared to the control group. However, the non-interactive solution (M=2.94; SD=.827) is responsible for a lower product return probability than the interactive solution. When it came to the willingness to order the recommended size (by the VFR) or one size larger (by the size recommendation), the interactive group demonstrated slightly higher trust in the recommendation (M=1.55; SD=.605) compared to the non-interactive group (M=2.06; SD=.827). Therefore, these further descriptive insights revealed a different perception of AI & Co. technologies regarding the sustainability consciousness of the consumer when online shopping fashion. Sustainability-unconscious consumers do not show a difference in their perception regarding interactivity, whereas sustainability-conscious respondents do. However, these results can only be considered to a limited extent due to the small sample sizes in the sustainability-conscious and sustainability-unconscious subgroups. In addition, inductive studies are essential in order to check whether these observations occurred by chance or whether they are justified.

Table 14 Descriptive Statistics: Product return likelihood of sustainability-conscious vs. sustainability-unconscious participants (N_{Sus_uncon}=58, N_{Sus_con}=54)

5-point Likert Scale: 1=very likely to return; 5=very unlikely to return

	Sustainability-unconscious			Sustainability-conscious		
	N	M	SD	N	M	SD
Control	22	2,64	1,093	14	2,29	1,437
Interactive	22	3,32	,716	23	3,70	1,020
Non-interactive	14	3,29	,994	17	2,94	,827

Source: Own presentation

In summary, the most common reasons given by the sample for product returns in fashion e-commerce occur at the pre-purchase stage and underline the relevance of PPRM. The most frequently cited reason is an improper product fit, as found in the literature. Furthermore, the descriptive evaluation of product return behavior did not reveal any gender differences regarding the frequency of returning products as well as shopping online. In addition, the hypothesis tests supported that interactive and non-interactive AI & Co. solutions significantly reduce the likelihood of product returns at the customer interface. However, interactive solutions reduce the likelihood of product returns even more so than non-interactive solutions. Furthermore, there is a difference in the perception of these problem-solving technologies between customers who buy sustainable fashion and those who do not.

6 Discussion

The following section includes an interpretation of the online experiment's results as well as it provides managerial implications. Moreover, suggestions on further research and limitations of this study will be given.

6.1 Interpretation of the results

Regarding the triggers of product returns, the findings of this study align with those of Leong et al. (2023), as presented in section 3.3. The sample ($N_{Total\_Sample\_Cleaned}$=112) revealed that the main reasons for product returns are related to sizing, personal style, product display and product description. As stated in section 3.3.1, these are drivers for product returns that could be addressed before an order is placed. Consequently, these results emphasize the importance of implementing preventive measures to manage returns at the pre-purchase stage.

Coming back to the research questions formulated in section 1.2, all three of them can be answered based on the results of this study.

> **RQ1:** *Can AI and Co. solutions be implemented at the customer interface to reduce product returns in e-commerce?*

The study revealed that AI & Co. solutions that are implemented at the customer interface significantly reduce product returns. However, during the literature review process, it was investigated that these solutions differ in their interactivity. As for interactive AI & Co. solutions, two main measures were found: VTO solutions as well as Chatbots. These solutions require active data insertion by the customer, e.g. body measurements or questions about the product. By referencing said data, the interactive solution can support the buying decision and effectively minimize the likelihood of product returns. Non-interactive solutions, on the other hand, do not require any actively inserted data. The results of these solutions are based on data that has been collected and analyzed in the backend so that the customer simply receives the output that aims to reduce the likelihood of product returns. These non-interactive solutions are automated product descriptions, size recommendations and product recommendations. However, product recommendations should be considered cautiously in the context of product return reduction. As a result, the study aimed to discover whether interactive or non-interactive solutions reduce the likelihood of product returns more. Thus, RQ2 was formulated:

RQ2: *Which AI & Co. solutions that can be implemented at the customer interface are most likely approved to reduce them?*

During the literature review phase, it was found that interactive solutions address multiple drivers of product returns compared to non-interactive solutions. Each of the latter solutions addresses only one product return driver.
Therefore, the assumption was made that interactive AI & Co. solutions reduce the likelihood of product returns more so than non-interactive solutions. This assumption was supported based on the experiment's collected data and the tested hypotheses. As a result, the interactive AI & Co. solutions VTOs and chatbots are most likely approved to reduce product returns. However, it is worth reiterating that VTO solutions can be divided into AR-based VTO solutions, such as this one from Mister Spex (Mister Spex, 2023a), and VR-based VFRs, such as this one from Hugo Boss (Hugo Boss, 2023). As AR-based VTO solutions are not yet well developed, especially for the apparel market, VR-based VFRs are recommended over AR-based VTO solutions.
This result leads to the final research question that was:

RQ3: *Is there a difference in the perception of interactive and non-interactive AI & Co. solutions between sustainability-conscious and sustainability-unconscious consumers?*

On the one hand, this study revealed that sustainability-conscious customers rated the likelihood of returning products higher with the implementation of interactive solutions rather than with non-interactive solutions. Thus, sustainability-conscious consumers prefer informed buying decisions through interactive solutions. On the other hand, consumers who lack awareness concerning sustainability showed no difference in the effectiveness of reducing returns based on interactivity. This means that both interactive and non-interactive solutions are equally effective in reducing the likelihood of product returns for them.

6.2 Implication for practice

In the following, the implication for practice and recommendations for preventive measures at the customer interface will be given. Since product returns pose significant challenges for brands by causing environmental and operational costs, which in turn reduce customer satisfaction and overall brand reputation, brands must implement strategies to effectively reduce product returns (bevh, 2023; Heering & Rock, 2022; Möhring et al., 2015).

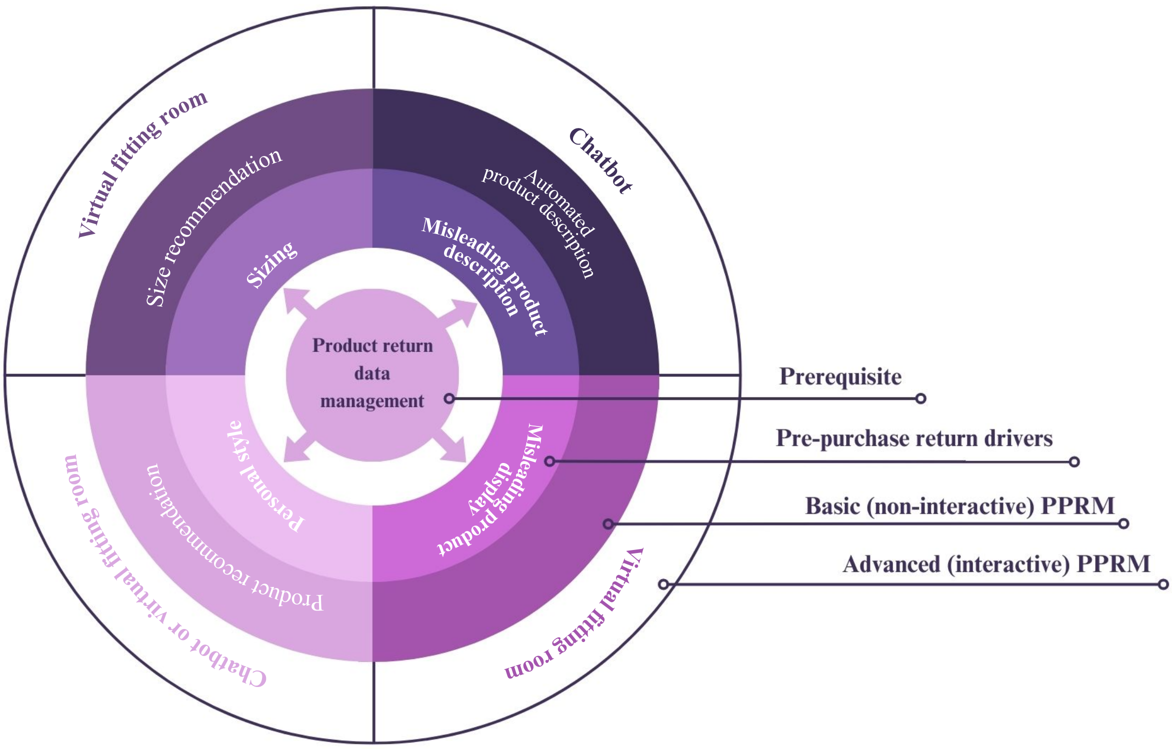
In order to effectively address said product returns, brands should analyze the drivers behind the customers' product returns related to their own brand as these drivers for product returns may vary for brand specific-reasons. For instance, customers may experience sizing issues because a brand's sizes consistently run smaller than usual. One way to determine why customers return products is by asking for and collecting post-return data. Conducting regular surveys addressed to the brand's regular shoppers would also help investigate the issue. By understanding the customer's triggers for product returns, brands can tailor their PPRM strategy accordingly (Leong et al., 2023).

Once product return reasons' data management is complete, the brands should reflect on their available resources for the implementation and maintenance phase for the preventive measures, including financial, time and human resources. This evaluation is necessary to guarantee seamless integration into the customer interface since this affects the decision for either interactive or non-interactive solutions. Interactive solutions might generally require more resources due to their novelty. However, interactive solutions have proven to be more effective in reducing product returns in comparison to non-interactive solutions.

The study's descriptive results also revealed that considering the target group's sustainability consciousness might be strategically important in PPRM. If the target group values sustainability, an interactive solution might be the better choice since interactive solutions engage customers, enabling them to make informed buying decisions (Han et al., 2017). In addition, the Corporate Social Responsibility Directive (CSRD) was introduced in January 2023 and will soon require all companies to disclose their internal environmental, social and governance (ESG) data (European Parliament, 2022). Given the significant environmental impact of product returns and the pollution that they cause, these will also affect the ESG report. Therefore, the impact of product returns will be disclosed in a comparable manner because of the CSRD introduction. This means, on the one hand, that it makes sense for all companies, sustainable or not, to implement AI & Co. solutions to reduce product returns. On the other hand, brands that are positioning themselves as sustainable should take on the extra effort to implement interactive solutions, as they are proven to be significantly more efficient at reducing returns.

Based on the analysis of the brand's drivers for product returns and its available resources, appropriate interactive or non-interactive solutions can be selected while considering the brand's sustainability positioning.
A managerial implication framework has been developed to support managers in implementing preventive measures at the customer interface to reduce product returns (figure 11).

Figure 11 Managerial implication framework for PPRM at the customer interface



Source: Own presentation

If a brand is considering implementing interactive AI & Co. measures, they should be aware of some critical details due to the novelty of these solutions. It is necessary to provide a clear explanation of how to use the interactive solution to ensure ease of use. Moreover, developers should consistently work on the technical details to ensure a seamless user experience. Building trust around the new feature will also be necessary. This can be achieved, e.g., through user reviews, highlighting positive experiences and successful outcomes with the interactive solution.
Due to the variety of reasons for product returns, it is also advisable to implement not just one but several AI & Co. solutions. This should be weighed against the available resources and the company's most popular drivers for product returns.

As a result, depending on the brand's capacities, the most popular reasons for product returns and the brand’s sustainability positioning, the corresponding interactive or non-interactive AI & Co. solution can be chosen. Nevertheless, it is essential to emphasize that the most crucial action for brands should be to start the process of PPRM and address product returns, as both the implementation of an interactive or non-interactive solution will reduce the likelihood of product returns. However, further research is required to provide more details on PPRM and the role of interactivity in AI & Co. solutions to tackle product returns at the customer interface.

6.3 Limitations of the research and further research

This study has some limitations which will be investigated in the following. Due to the small sample size ($N_{Total\_Sample\_Cleaned}$=112) and its disproportionate representation of students and Gen Z, the sample is not representative of a cross-section of the (German) population. Thus, the experiment could be replicated with a larger, more diverse sample. However, this study provided the first relevant insights into the role of interactivity and its impact on reducing product returns.

Additionally, there remains a lack of a detailed product return query on the German market since not all reasons for product returns were covered in this survey as they have been exposed in chapter 3.2 by Saarijärvi et al. (2017). Representative and detailed insights into the reasons for product returns would support further insights into PPRM. Moreover, it would be interesting to conduct a deeper investigation of further variables such as the role of the customer’s sustainability awareness or gender which might influence the reasons for product returns.

Additionally, this study investigated only two AI & Co. solutions, each representing interactive and non-interactive solutions. Consequently, the other technical solutions should also be tested. If the results are similar regarding the role of interactivity, an in-depth comparison regarding each solution should be made. Due to the fact that some drivers for product returns can be tackled not only by one AI & Co. solution, it would also be interesting to conduct studies that look at the efficiency of each AI & Co. solution in reducing each driver separately from one another. For example, the research question regarding the sizing driver would be: “Are VFRs or size recommendations more efficient in reducing the sizing driver?". In this study, however, the effects of AI & Co. solutions on individual drivers for product returns were not considered separately.

Regarding the result of this study that interactive solutions reduce the likelihood of product returns significantly more so than non-interactive solutions, more detailed research on interactive solutions and specifically their technical development should be done. Due to the early stage of development of these problem-solving technologies, it should be investigated how these technologies can be best implemented by improving the user experience. Also, it should be investigated how to engage the customer, so they take time to use the interactive tool properly when shopping online.

Additionally, this study only observed the hypothetical likelihood of returning a product purchased from the online store *Sewy.* It is possible that a real-life experiment with physical products would yield different results.

Besides, the descriptive analysis of the study showed that customers who do not value sustainability when buying fashion online do not show a significant difference in their likelihood of reducing product returns when differentiating between interactive and non-interactive solutions. However, customers who value sustainability show a different result and rate the likelihood of reducing returns differently. Therefore, further investigation by testing the following propositions (P) could be done:

> **P1:** *Among sustainability-unconscious consumers, interactive and non-interactive AI & Co. solutions reduce the likelihood of product returns. However, there is no significant difference in the likelihood of reducing product returns between these solutions.*
>
> **P2:** *Among sustainability-conscious consumers, interactive AI & Co. solutions reduce the likelihood of product returns significantly more than non-interactive AI & Co. solutions.*

In summary, in the fashion industry, PPRM research is still in its early stages. However, given the dynamic nature of the market and the environmental urgency to reduce pollution and waste within the industry, it is more urgent than ever that brands continue to address the issue of product returns and take action to reduce them.

List of references

Accenture. (2018). Returns the value conundrum—Accenture Post and Parcel Industry Research 2018. https://www.accenture.com/_acnmedia/PDF-95/Accenture-Postal-Vision-2020-Returns-Slideshare.pdf (Accessed on 15.06.2023).

Alpaydin, E. (2022). Maschinelles Lernen. De Gruyter: Oldenburg.

Asdecker, B. (2014). Retourenmanagement im Versandhandel: Theoretische und empirisch fundierte Gestaltungsalternativen für das Management von Retouren (Vol. 10). University of Bamberg Press: Bamberg.

Asdecker, B. (2023). Retourenvermeidung Definition. Retourenforschung. http://www.retourenforschung.de/definition_retourenvermeidung.html (Accessed on 21.05.2023).

Ashfaq, M., Yun, J., Yu, S., & Loureiro, S. M. C. (2020). I, Chatbot: Modeling the determinants of users' satisfaction and continuance intention of AI-powered service agents. Telematics and Informatics, Vol. 54, p. 101473.

AX Semantics. (2021). How Mytheresa Improves SEO with Automated Content. https://en.ax-semantics.com/case-study/mytheresa/ (Accessed on 21.06.2023).

Baştanlar, Y., & Özuysal, M. (2014). Introduction to Machine Learning. In M. Yousef (Ed.), MiRNomics: MicroRNA Biology and Computational Analysis, Vol. 1107, pp. 105–128. Humana Press.

Baumgarth, C., & Binckebanck, L. (2015). Building and managing CSR brands—Theory and applications. Proceedings, Corporate Social Responsibility & Sustainable Business Development, Ho-Chi-Minh-City, pp. 35–51.

Bergmann, H., Stüber, E., & Strathmann, M. (2013). Versand- und Retourenmanagement im E-Commerce—Handelstrends und Konsumentenerwartung. EHI Retail Institute: Köln.

Berman, S. (2023). Der komplette Leitfaden für Retouren Marketing im Handel. ParcelLab. https://parcellab.com/de/blog/was-ist-retail-retouren-marketing?locale=de (Accessed on 14.05.2023).

bevh. (2023). Bevh-Retourenkompendium (G. Prof. Dr. Heinemann & A. Mulyk, Eds.). bevh. https://www.bevh.org/fileadmin/content/04_politik/Nachhaltigkeit/Retouren-kompendium/Final_2._Auflage_Retourenkompendium_41_.pdf (Accessed on 05.06.2023).

Burke, R. R. (2002). Technology and the customer interface: What consumers want in the physical and virtual store. Journal of the Academy of Marketing Science, Vol. 30(4), pp. 411–432.

Buxmann, P. (2019). Künstliche Intelligenz: Mit Algorithmen zum wirtschaftlichen Erfolg. (H. Schmidt, Ed.) Springer Gabler: Wiesbaden.

Carmigniani, J., & Furht, B. (2011). Augmented reality: An overview. Handbook of Augmented Reality, pp. 3–46.

Chakraborty, S., Hoque, M. S., Rahman Jeem, N., Biswas, M. C., Bardhan, D., & Lobaton, E. (2021). Fashion recommendation systems, models and methods: A review. Informatics MDPI, Vol. 8(3), p. 49.

Chen, J.-S., Le, T.-T.-Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. International Journal of Retail & Distribution Management, Vol. 49(11), pp. 1512–1531.

Chintalapati, S., & Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. International Journal of Market Research, Vol. 64(1), pp. 38–68. Business Source Ultimate.

Colliot, O. (2023). A non-technical introduction to machine learning. Machine Learning for Brain Disorders, p. 197.

Cui, L., Huang, S., Wei, F., Tan, C., Duan, C., & Zhou, M. (2017). Superagent: A customer service chatbot for e-commerce websites. Proceedings of ACL 2017, System Demonstration, pp. 97–102.

Cuomo, M. T., Tortora, D., Festa, G., Ceruti, F., & Metallo, G. (2020). Managing omni-customer brand experience via augmented reality. Qualitative Market Research: An International Journal, Vol. 23(3), pp. 427–445.

Deges, F. (2017). Retourenmanagement im Online-Handel: Kundenverhalten beeinflussen und Kosten senken. Springer Gabler: Wiesbaden.

Dizdarevic, A. (2022). Immersive Experiences in Retail Agglomerations: The Diffusion of Virtual and Augmented Reality Technologies. In Der zukunftsfähige Handel: Neue online und offline Konzepte sowie digitale und KI-basierte Lösungen (pp. 67–81). Springer Gabler: Wiesbaden.

Dobrev, D. (2012). A definition of artificial intelligence. Mathematica Balkancia, Vol. 19, pp. 67–74.

Dopson, E. (2021). Ecommerce Returns: Expert Guide to Best Practices. Shopify. https://www.shopify.com/enterprise/ecommerce-returns#1 (Accessed on 25.06.2023).

European Parliament. (2022). Directive (EU) 2022/2464 of the European Parliament and of the Council of 14 December 2022 amending Regulation (EU) No 537/2014, Directive 2004/109/EC, Directive 2006/43/EC and Directive 2013/34/EU, as regards corporate sustainability reporting (Text with EEA relevance). EUR-Lex. http://data.europa.eu/eli/dir/2022/2464/oj/eng (Accessed on 19.06.2023).

Grand View Research. (2022). E-commerce Apparel Market Size, Share & Trends Analysis Report. Grand View Research. https://www.grandviewresearch.com/industry-analysis/e-commerce-apparel-market-report (Accessed on 19.05.2023).

Guigourès, R., Ho, Y. K., Koriagin, E., Sheikh, A.-S., Bergmann, U., & Shirvany, R. (2018). A hierarchical bayesian model for size recommendation in fashion. Proceedings of the 12th ACM Conference on Recommender Systems, pp. 392–396.

Hahn, S., & Scholz, M. (2020). Wie Maschinen lernen. Innovative Verwaltung, Vol. 42(4), pp. 27–29.

Han, S. L.-C., Henninger, C. E., Apeagyei, P., & Tyler, D. (2017). Determining effective sustainable fashion communication strategies. Sustainability in Fashion: A Cradle to Upcycle Approach, pp. 127–149.

Handelsverband Deutschland, & IFH Köln. (2022). Online Monitor 2022. Handelsverband Deutschland. https://einzelhandel.de/index.php?option=com_attachments&task=download&id=10659 (Accessed on 05.06.2023).

Harreis, H., Koullias, T., Roberts, R., & Te, K. (2022). Generative AI in fashion. McKinsey. https://www.mckinsey.com/industries/retail/our-insights/generative-ai-unlocking-the-future-of-fashion (Accessed on 12.06.2023).

Harwardt, M., & Köhler, M. (2023). KI im E-Commerce. In Künstliche Intelligenz entlang der Customer Journey: Einsatzpotenziale von KI im E-Commerce (pp. 31–41). Springer Gabler: Wiesbaden.

Heering, I., & Rock, S. (2022). Retourenmanagement im Onlinehandel: Quelle zur Steigerung der Kundenzufriedenheit. In M. Knoppe, S. Rock, & M. Wild (Eds.), Der zukunftsfähige Handel: Neue online und offline Konzepte sowie digitale und KI-basierte Lösungen (pp. 391–413). Springer Gabler: Wiesbaden.

Heinemann, G. (2022). Der neue online-Handel (13th ed.). Springer Gabler: Wiesbaden.

Heins, C. (2022). Artificial intelligence in retail–a systematic literature review. Foresight, Vol. 25(2), pp. 264–286.

Henkel, R. (2020). 5 Tipps zur Reduzierung der Retourenquote durch mehr Personalisierung. Fashion United. https://fashionunited.de/nachrichten/einzelhandel/5-tipps-zur-reduzierung-der-retourenquote-durch-mehr-personalisierung/2020090737010 (Accessed on 09.06.2023).

Hielscher, H. (2021). Hugo Boss: „Was LVMH im Luxusbereich macht, könnten wir im Premiumsegment“. Wirtschaftswoche. https://www.wiwo.de/unternehmen/handel/hugo-boss-was-lvmh-im-luxusbereich-macht-koennten-wir-im-premiumsegment/27600732.html (Accessed on 21.06.2023).

Hughes, H. (2022). Hugo Boss introduces virtual reality dressing rooms for online shopping. Fashion United. https://fashionunited.com/news/retail/hugo-boss-introduces-virtual-reality-dressing-rooms-for-online-shopping/2022080248958 (Accessed on 15.06.2023).

Hugo Boss. (2023). Virtual Dressing Room. Hugo Boss. https://www.hugoboss.com/on/demandware.store/Sites-UK-Site/en_GB/Dressing Room-Welcome (Accessed on 28.06.2023).

Hussy, W., Schreier, M., & Echterhoff, G. (2013). Forschungsmethoden in Psychologie und Sozialwissenschaften für Bachelor Research methods in psychology and social sciences for the bachelor’s degree. Springer International Publishing: Heidelberg.

ibi research. (2017). Trends und Innovationen beim Versand – Was erwartet der Kunde?. Ecommerce Leitfaden. https://www.ecommerce-leitfaden.de/studien/item/trends-und-innovationen-beim-versand-was-erwartet-der-kunde (Accessed on 01.04.2023).

Jayaswal, P., & Parida, B. (2023). The role of augmented reality in redefining e-tailing: A review and research agenda. Journal of Business Research, Vol. 160, p. 113765.

Jerald, J. (2015). The VR book: Human-centered design for virtual reality. Morgan & Claypool: Waterloo.

Jung, S., & Jin, B. (2014). A theoretical investigation of slow fashion: Sustainable future of the apparel industry. International Journal of Consumer Studies, Vol. 38(5), pp. 510–519.

Kersting, K., Lampert, C., & Rothkopf, C. (2019). Wie Maschinen lernen. Springer Gabler: Wiesbaden.

Kirkby, A., Baumgarth, C., Henseler, J., & Butzer-Strothmann, K. (2022). Soziale Künstliche Intelligenz für die Markenstimme – KIMS-Matrix als Orientierungsrahmen. In Integriertes Online-und Offline-Channel-Marketing: Praxisbeispiele und Handlungsempfehlungen für das Omni-Channel-Marketing (pp. 173–189). Springer Gabler: Wiesbaden.

Kreutzer, R. T., & Sirrenberg, M. (2020). Understanding artificial intelligence. Springer International Publishing: Berlin.

Lämmermühle, P. (2016). Betrachtung und Analyse aktueller Konzepte, Technologien und Systeme des Retourenmanagements im E-Commerce. Schriftenreihe Des Lehrstuhls Für Logistikmanagement Universität Bremen, Vol. 4.

Lasserre, J., Sheikh, A.-S., Koriagin, E., Bergman, U., Vollgraf, R., & Shirvany, R. (2020). Meta-learning for size and fit recommendation in fashion. Proceedings of the 2020 SIAM International Conference on Data Mining, pp. 55–63.

Lee, H., & Xu, Y. (2020). Classification of virtual fitting room technologies in the fashion industry: From the perspective of consumer experience. International Journal of Fashion Design, Technology and Education, Vol. 13, pp. 1–10.

Lee, H., Xu, Y., & Porterfield, A. (2022). Virtual Fitting Rooms for Online Apparel Shopping: An Exploration of Consumer Perceptions. Family & Consumer Sciences Research Journal, Vol. 50(3), pp. 189–204.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of marketing, Vol. 80(6), pp. 69-96.

Leong, C., Wu, E., Federowski, R., & Gehin, S. (2023). Solving fashion’s product returns How to keep value in a closed-loop system. Institute of Positive Fashion. https://instituteofpositivefashion.com/uploads/files/1/Report---Solving-fashion's-product-returns-March-2023.pdf (Accessed on 05.06.2023).

Mc Gowran, L. (2023). Zalando turns to ChatGPT to make an AI fashion assistant. Silicon Republic. https://www.siliconrepublic.com/machines/zalando-chatgpt-ai-fashion-assistant (Accessed on 01.07.2023).

McKinsey & Company, & Global Fashion Agenda. (2020). Fashion on Climate. McKinsey. https://www.mckinsey.com/industries/retail/our-insights/fashion-on-climate (Accessed on 10.05.2023).

Merle, A., Senecal, S., & St-Onge, A. (2012). Whether and How Virtual Try-On Influences Consumer Responses to an Apparel Web Site. International Journal of Electronic Commerce, Vol. 16(3), pp. 41–64.

Merle, A., Sénécal, S., & St-Onge, A. (2018). Miroir, mon beau miroir, facilite mes choix! L'influence de l'essayage virtuel dans un contexte omnicanal. Decisions Marketing, Vol. 91, pp. 79–95.

Mister Spex. (2023a). Brille online anprobieren: Teste den virtuellen 3D-Simulator. Mister Spex. https://www.misterspex.de/l/pg/100508 (Accessed on 17.06.2023).

Mister Spex. (2023b). Virtuelle Anprobe. Mister Spex. https://corporate.misterspex.com/wp-content/uploads/2016/09/mister-spex-virtuelle-anprobe.jpg (Accessed on 17.06.2023).

Mohammadi, S. O., & Kalhor, A. (2021). Smart fashion: A review of AI applications in virtual try-on & fashion synthesis. Journal of Artificial Intelligence, Vol. 3(4), p. 284.

Möhring, M., Walsh, G., Schmidt, R., & Ulrich, C. (2015). Moderetouren im Deutschen Onlinehandel – Eine empirische Untersuchung. HMD Praxis Der Wirtschaftsinformatik, Vol. 52(2), pp. 257–266.

Moriuchi, E., Landers, V. M., Colton, D., & Hair, N. (2021). Engagement with chatbots versus augmented reality interactive technology in e-commerce. Journal of Strategic Marketing, Vol. 29(5), pp. 375–389.

Morletto, E. (2022). Hugo Boss launches virtual fittings. Luxury Tribune. https://www.luxurytribune.com/en/hugo-boss-launches-virtual-fittings (Accessed on 23.06.2023).

Optoro. (2020). Impact Report Powering Resilient Retail 2020. https://info.optoro.com/hubfs/The%20Optoro%202020%20Impact%20Report.pdf (Accessed on 12.06.2023).

Perannagari, K. T., & Chakrabarti, S. (2020). Factors influencing acceptance of augmented reality in retail: Insights from thematic analysis. International Journal of Retail & Distribution Management, Vol. 48(1), pp. 18–34.

Pristl, A.-C., & Mann, A. (2021). Retouren beim Online-Shopping: Gründe, Auswirkungen und Implikationen für die Produktpräsentation und -kommunikation im E-Commerce. Transfer: Zeitschrift Für Kommunikation & Markenmanagement, Vol. 67, pp. 70–77.

Raab, G., Unger, F., & Unger, A. (2018). Methoden der Marketing-Forschung: Grundlagen und Praxisbeispiele. Springer Gabler: Wiesbaden.

Reactive Reality. (2023a). Company—Reactive Reality. https://www.reactivereality.com/company (Accessed on 05.06.2023).

Reactive Reality. (2023b). Homepage. https://www.reactivereality.com/ (Accessed on 05.06.2023).

Roggeveen, A. L., & Sethuraman, R. (2020). Customer-interfacing retail technologies in 2020 & beyond: An integrative framework and research directions. Journal of Retailing, Vol. 96(3), pp. 299–309.

Roy, D., Srivastava, R., Jat, M., & Karaca, M. S. (2022). A complete overview of analytics techniques: Descriptive, predictive, and prescriptive. Decision Intelligence Analytics and the Implementation of Strategic Business Management, pp. 15–30.

Russell, S. J., & Norvig, P. (2012). Künstliche Intelligenz: Ein moderner Ansatz. Pearson Studium: München.

Saarijärvi, H., Sutinen, U.-M., & Harris, L. C. (2017). Uncovering consumers' returning behaviour: A study of fashion e-commerce. The International Review of Retail, Distribution and Consumer Research, Vol. 27(3), pp. 284–299.

Scheier, C., & Held, D. (2019). Künstliche Intelligenz in der Markenführung: Der effiziente Weg den Erfolg von Marken zu steuern. Haufe-Lexware: Freiburg.

Seo, J. Y., Yoon, S., & Vangelova, M. (2016). Shopping plans, buying motivations, and return policies: Impacts on product returns and purchase likelihoods. Marketing Letters, Vol. 27, pp. 645–659.

Sheikh, A.-S., Guigourès, R., Koriagin, E., Ho, Y. K., Shirvany, R., Vollgraf, R., & Bergmann, U. (2019). A deep learning system for predicting size and fit in fashion e-commerce. Proceedings of the 13th ACM Conference on Recommender Systems, pp. 110–118.

Siau, K., & Yang, Y. (2017). Impact of artificial intelligence, robotics, and machine learning on sales and marketing. Twelve Annual Midwest Association for Information Systems Conference (MWAIS 2017), Vol. 48, pp. 18–19.

Soliman, M., Peetz, J., & Davydenko, M. (2017). The impact of immersive technology on nature relatedness and pro-environmental behavior. Journal of Media Psychology, Vol. 29, pp. 8–17.

Stahl, E., Wittmann, G., Krabichler, T., & Breitschaft, M. (2012). E-Commerce-Leitfaden: Noch erfolgreicher im elektronischen Handel (3rd ed.). Universitätsverlag Regensburg: Regensburg.

Stöcker, B., Baier, D., & Brand, B. M. (2021). New insights in online fashion retail returns from a customers' perspective and their dynamics. Journal of Business Economics, Vol. 91(8), pp. 1149–1187.

Suh, A., & Prophet, J. (2018). The state of immersive technology research: A literature analysis. Computers in Human Behavior, Vol. 86, pp. 77–90.

trbo. (2023). Homepage. Trbo. https://www.trbo.com/de/ (Accessed on 08.07.2023).

Tucker, S. (2008). E-commerce standard user interface: An E-menu system. Industrial Management & Data Systems, Vol. 108(8), pp. 1009–1028.

Unipark. (2023). Homepage. Unipark. https://www.unipark.com/ (Accessed on 15.06.2023).

Vue. (2023). Virtual Dressing Room for eCommerce. Vue. https://vue.ai/products/virtual-dressing-room/ (Accessed on 15.06.2023).

Walsh, G., Möhring, M., Koot, C., & Schaarschmidt, M. (2014). Preventive Product Returns Management Systems: A Review and a Model. ECIS 2014 Proceedings - 22nd European Conference on Information Systems, pp. 1-12.

Wang, W., & Siau, K. (2019). Artificial intelligence, machine learning, automation, robotics, future of work and future of humanity: A review and research agenda. Journal of Database Management (JDM), Vol. 30(1), pp. 61–79.

Welivita, A., Nimalsiri, N., Wickramasinghe, R., Pathirana, U., & Gamage, C. (2017). Virtual product try-on solution for e-commerce using mobile augmented reality. Augmented Reality, Virtual Reality, and Computer Graphics: 4th International Conference, AVR 2017, Ugento, Italy, June 12-15, 2017, Proceedings, Part I 4, pp. 438–447.

Wix. (2023). Homepage. Wix. https://de.wix.com (Accessed on: 13.05.2023).

Wohlgenannt, I., Simons, A., & Stieglitz, S. (2020). Virtual reality. Business & Information Systems Engineering, Vol. 62, pp. 455–461.

Zalando. (2023). Zalando to launch a fashion assistant powered by ChatGPT. https://corporate.zalando.com/en/technology/zalando-launch-fashion-assistant-powered-chatgpt (Accessed on: 24.06.2023).

Zhang, T., Wang, W. Y. C., Cao, L., & Wang, Y. (2019). The role of virtual try-on technology in online purchase decision from consumers' aspect. Internet Research, Vol. 29(3), pp. 529–551.

Zhou, W., Hinz, O., & Benlian, A. (2018). The impact of the package opening process on product returns. Business Research, Vol. 11, pp. 279–308.

Appendix

Appendix I: Online experiment survey

Fragebogen

1 Demographische Fragen

Bitte geben Sie Ihr Geschlecht an.

(Pflichtfrage)

- ◯ Weiblich
- ◯ Männlich
- ◯ Divers

Welche Tätigkeit üben Sie aus?

(Pflichtfrage)

- ◯ Schüler*in
- ◯ Auszubildende*r
- ◯ Student*in
- ◯ Angestellte*r
- ◯ Beamte*r
- ◯ Freiberufler*in
- ◯ Hausfrau/Hausmann
- ◯ Rentner*in
- ◯ Ohne Beschäftigung

Wo sind Sie aktuell wohnhaft?

(Pflichtfrage)

- ◯ In Deutschland
- ◯ Außerhalb von Deutschland

Wie hoch ist Ihr monatliches Nettoeinkommen?

(Pflichtfrage)

- ◯ <1.000 Euro
- ◯ 1.000 - 2.000 Euro
- ◯ 2.000 – 3.000 Euro
- ◯ 3.000 – 5.000 Euro
- ◯ 5.000 – 10.000 Euro
- ◯ >10.000 Euro

Zu welcher der nachfolgenden Alterskategorien gehören Sie?

(Pflichtfrage)

- ◯ Jünger als 18 Jahre
- ◯ 18-26 Jahre
- ◯ 27-43 Jahre
- ◯ 44-58 Jahre
- ◯ 59-77 Jahre
- ◯ 78 Jahre oder älter

Bitte wählen Sie Ihren Geburtsmonat aus.

(Pflichtfrage)

- ◯ Mein Geburtstag ist im / liegt zwischen Januar und April.
- ◯ Mein Geburtstag ist im / liegt zwischen Mai und August.
- ◯ Mein Geburtstag ist im / liegt zwischen September und Dezember.

2 Kaufverhalten Onlineshopping

Wie wichtig ist Ihnen der Aspekt der Nachhaltigkeit, wenn Sie Bekleidung kaufen?

(Pflichtfrage)

Sehr wichtig ◯ ◯ ◯ ◯ ◯ Sehr unwichtig

Wie häufig kaufen Sie neue Bekleidungsartikel online ein?

(Pflichtfrage)

- Mehrmals im Monat
- Etwa einmal im Monat
- Etwa einmal alle drei Monate
- Etwa einmal alle sechs Monate
- Seltener

3 "Retouren" Erläuterung

In dieser Umfrage wird häufig die Rede von **„Retouren“** sein. Darunter fallen lediglich **Retouren, die beim Kauf von neuen Bekleidungsartikeln aus Online-Shops** entstanden sind.

Darunter fallen alle Bekleidungsstücke **AUßER Unterwäsche, Socken, Luxusartikel, sowie Accessoires und Schuhe.**

4 Retoureverhalten

Wie oft senden Sie online bestellte Bekleidungsartikel zurück?

(Pflichtfrage)

- Ich retourniere **regelmäßig** online bestellte Bekleidungsartikel **(bei jeder oder jeder zweiten Bestellung).**
- **Gelegentlich** retourniere ich online bestellte Bekleidungsartikel **(bei jeder dritten Bestellung oder seltener).**
- Ich retourniere **nie** online bestellte Bekleidungsartikel.

Wie sehr bemühen Sie sich aktiv Retouren zu vermeiden, wenn Sie online Bekleidungsartikel bestellen?

(Pflichtfrage)

- Ich **gebe mir große Mühe,** nur Artikel zu bestellen, die ich behalten werde.
- Ich **versuche darauf zu achten,** bin aber noch nicht konsequent damit.
- Nein, ich **achte nicht speziell darauf** bei meinen Bestellungen.

Ist Ihnen bekannt, was mit den Bekleidungsartikeln geschieht, die retourniert werden?
(Pflichtfrage)

- ○ **Ja, ich weiß,** was mit den retournierten Artikeln geschieht.
- ○ **Ich habe eine grobe Vorstellung,** weiß aber nicht im Detail, was mit den retournierten Artikeln geschieht.
- ○ **Nein, ich habe keine genaue Vorstellung** davon, was mit den retournierten Artikeln geschieht.

5 Retoure-Gründe

Bitte geben Sie an, in welchem Maße die folgenden Gründe bei Ihren Retouren zutreffen, indem Sie die entsprechende Option auswählen:
(Pflichtfrage)

	Trifft sehr stark zu				Trifft sehr schwach zu
Ein **anderes Produkt,** als das, was ich bestellt hatte, **wurde geliefert.**	○	○	○	○	○
Die Lieferung kam **zu spät** an.	○	○	○	○	○
Das Produkt **passte nicht** (war entweder zu klein oder zu groß).	○	○	○	○	○
Ich habe das **gleiche Produkt in verschiedenen Größen oder Farben bestellt,** mit der Absicht, nur eine Variante des Produkts zu behalten.	○	○	○	○	○
Das Produkt hat **nicht meinen Qualitäts-Erwartungen entsprochen.**	○	○	○	○	○
Das Produkt hat mir **nicht gefallen.**	○	○	○	○	○
Das Produkt war ein **spontaner Kaufimpuls**. Ich brauchte das Produkt gar nicht.	○	○	○	○	○
Ich habe es **bereut zu viel Geld ausgegeben** zu haben.	○	○	○	○	○
Ich habe das Produkt **einmal getragen und dann zurückgesendet.**	○	○	○	○	○
Die **Produktbeschreibung oder Produktdarstellung** im Onlineshop war **nicht realitätsgetreu.**	○	○	○	○	○
Das Produkt wurde **defekt geliefert.**	○	○	○	○	○
Ich habe aus Versehen **ein falsches Produkt bzw. eine falsche Größe/Farbe eines Produkts bestellt.**	○	○	○	○	○

6.1 Gruppe A

Im Folgenden wird Ihnen die Website des **Onlineshops *Sewy*** gezeigt. Bitte gehen Sie davon aus, dass Sie das präsentierte Produkt **zum Kauf in Betracht ziehen**. Bitte schauen Sie sich die Website mit ihren Funktionen genau an.

Onlineshop Sewy

(Bitte spielen Sie das Video ab)

6.2 Neutral Sewy

Wie viele Varianten (Größe/Farbe) des Artikels im Onlineshop Sewy würden Sie bestellen?

(Pflichtfrage)

- ○ Einen Artikel, da ich mir sicher wäre, welche Variante (Größe/Farbe) des Produkts ich kaufen würde.
- ○ Zwei oder mehr Varianten des Artikels, da ich noch unentschlossen wäre.

Wie wahrscheinlich ist es, dass Sie nach der Bestellung des Artikels/der Artikel im Onlineshop Sewy retournieren würden?

(Pflichtfrage)

Sehr wahrscheinlich	○	○	○	○	○	Sehr unwahrscheinlich

7.1 Gruppe B

Im Folgenden wird Ihnen die Website des **Onlineshops *Sewy*** gezeigt. Dieser bietet eine **virtuelle Anprobe** an. Bitte gehen Sie davon aus, dass Sie das präsentierte Produkt **zum Kauf in Betracht ziehen**. Bitte schauen Sie sich die Website mit ihren Funktionen genau an.

Onlineshop Sewy

mit integrierter virtueller Anprobe (Bitte spielen Sie das Video ab)

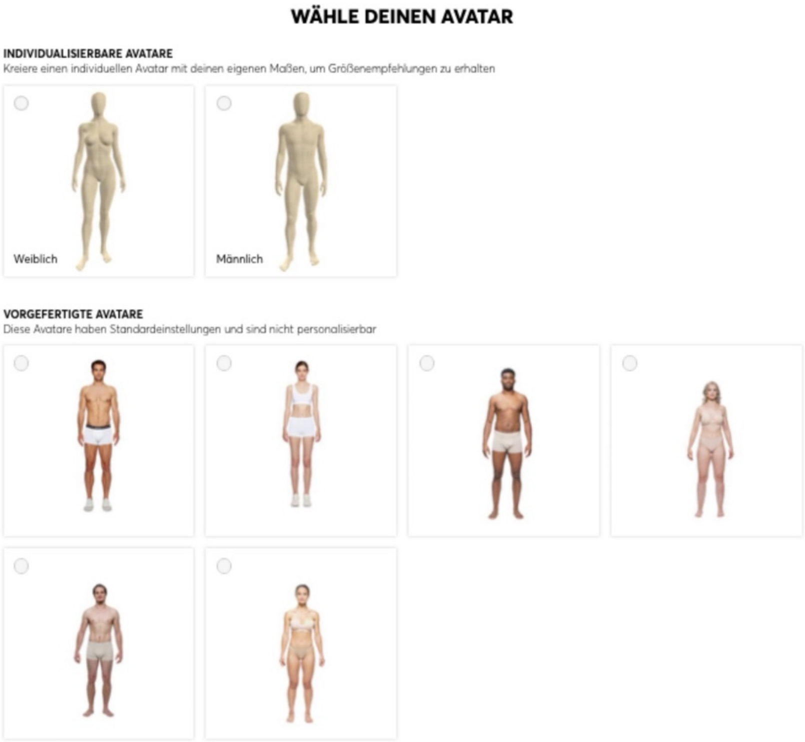
7.2 "Virtuelle Anprobe" Erläuterung

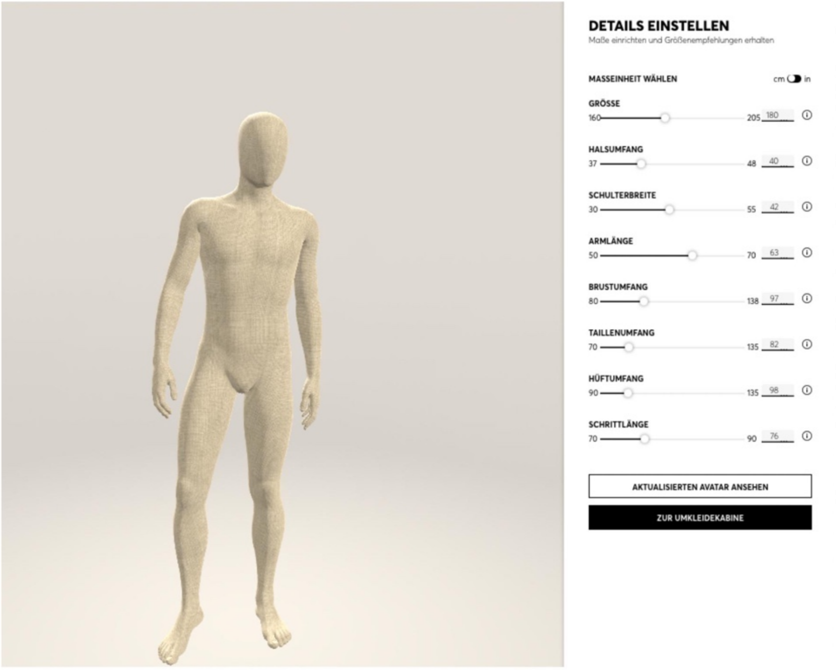
Die virtuelle Anprobe ermöglicht es Ihnen, das Kleidungsstück vor dem Kauf digital anzuprobieren. Das Ziel der virtuellen Anprobe ist es, die **Passform und die Gesamtwirkung des Kleidungsstücks vor dem Kauf besser einschätzen** zu können.

Bitte lesen Sie sich die nachfolgende Erläuterung zur Funktion der virtuellen Anprobe aufmerksam durch, um eine Vorstellung von dessen Bedienung zu bekommen, da Sie die virtuelle Anprobe in dieser Umfrage nicht ausprobieren können.
Im Anschluss folgen Fragen bezüglich der virtuellen Anprobe.

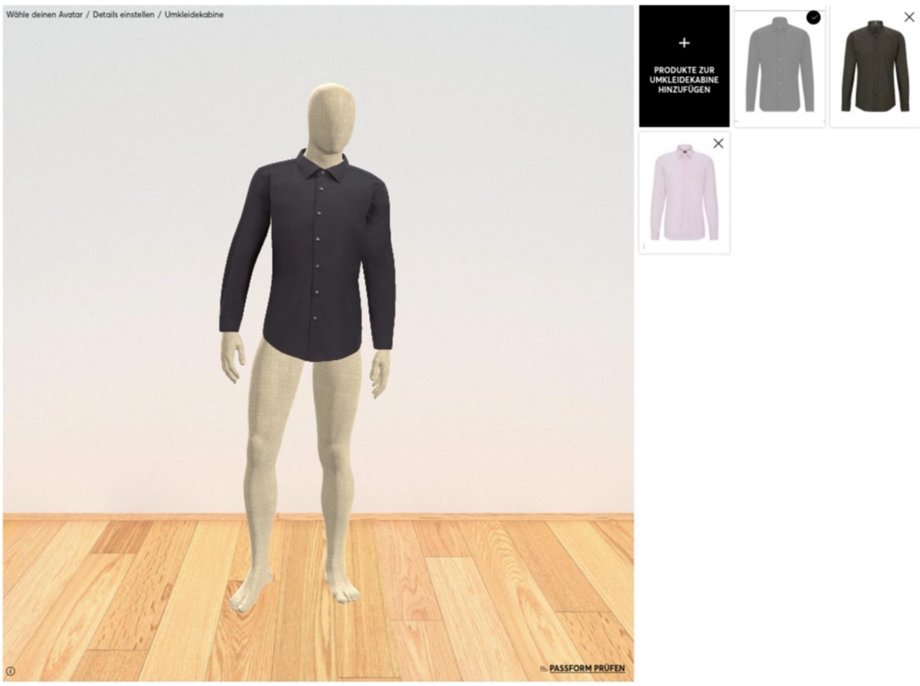
Die virtuelle Anprobe funktioniert wie folgt:

Schritt 1: Mit einem Klick auf den Button „Virtuelle Anprobe", den Sie im vorherigen Video gesehen haben, können Sie die virtuelle Anprobe des Onlineshops Sewy betreten. Es gibt zwei Optionen: Entweder Sie wählen einen **vorgefertigten Avatar,** der Ihrem Körpertyp ähnelt (diese Avatare sehen wie Menschen aus, sind aber standardisiert. Das bedeutet, dass Sie keine eigenen Körpermaße einstellen können und auch Haar- und Hautfarbe unveränderbar sind), oder Sie erstellen **Ihren persönlichen Avatar.** Für diese Avatare können Sie ihre Körpermaße eingeben. Der Avatar nimmt dadurch Ihre Figur an, allerdings haben diese kein Gesicht und Sie könnnen keine Haut- und Haarfarbe einstellen.

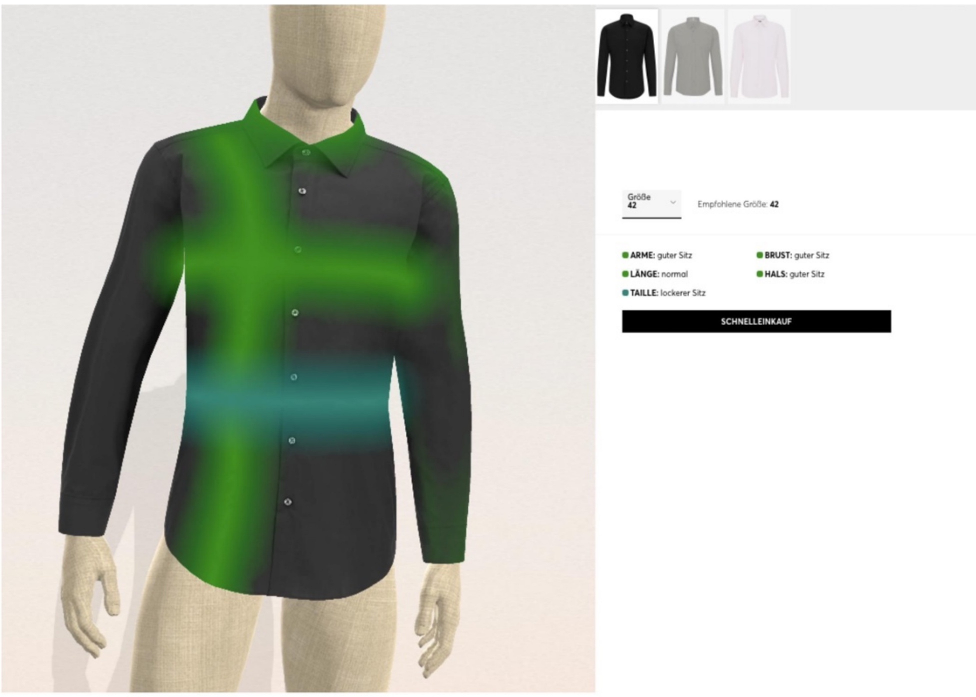

WÄHLE DEINEN AVATAR
INDIVIDUALISIERBARE AVATARE
Kreiere einen individuellen Avatar mit deinen eigenen Maßen, um Größenempfehlungen zu erhalten
Weiblich
Männlich
VORGEFERTIGTE AVATARE
Diese Avatare haben Standardeinstellungen und sind nicht personalisierbar



Schritt 2: Nun können Sie das **Produkt anprobieren**. Sie können mit Hilfe des Avatars sehen, wie das Kleidungsstück in verschiedenen Varianten an Ihnen aussehen würde. Hierbei können Sie Ihren **Avatar aus einem 360 Grad Blickwinkel** (von allen Seiten) betrachten.



Schritt 3: Mit dem Klick auf „Passform prüfen“ wird Ihnen **automatisch die passendste Größe** vorgeschlagen. Zudem erhalten Sie **Informationen zu der Passform des Produkts.**



Schritt 4: Nach der Anprobe können Sie die **Wunschvariante(n) des Produkts in den Warenkorb** legen und den Kauf abschließen.

7.3 Virtuelle Anprobe allgemein

Haben Sie schonmal eine virtuelle Anprobe bei einem früheren Online-Kauf genutzt?
(Pflichtfrage)

- ◯ Ja
- ◯ Nein

Könnten Sie es sich vorstellen, die virtuelle Anprobe im Onlineshop Sewy zu nutzen?
(Pflichtfrage)

- ◯ Ja
- ◯ Nein

7.4 Virtuelle Anprobe Sewy

Was ist der Grund/sind die Gründe dafür, dass Sie die virtuelle Anprobe im Onlineshop Sewy nicht nutzen würden?

(*Bei Nein:* Pflichtfrage)

Hätten Sie die Ihnen vorgeschlagene Größe der virtuellen Anprobe bestellt?

(Pflichtfrage)

Sehr wahrscheinlich ○ ○ ○ ○ ○ Sehr unwahrscheinlich

Wie viele Varianten (Größe/Farbe) des Artikels im Onlineshop Sewy würden Sie bestellen?

(Pflichtfrage)

- ○ Einen Artikel, da ich mir sicher wäre, welche Variante (Größe/Farbe) des Produkts ich kaufen würde.
- ○ Zwei oder mehr Varianten des Artikels, da ich noch unentschlossen wäre.

Wie wahrscheinlich ist es, dass Sie nach der Bestellung des Artikels/der Artikel im Onlineshop Sewy retournieren würden?

(Pflichtfrage)

Sehr wahrscheinlich ○ ○ ○ ○ ○ Sehr unwahrscheinlich

8.1 Gruppe C

Im Folgenden wird Ihnen die Website des **Onlineshops *Sewy*** gezeigt. Dieser bietet Ihnen eine **Größenempfehlung** an. Bitte gehen Sie davon aus, dass Sie das präsentierte Produkt **zum Kauf in Betracht ziehen**. Bitte schauen Sie sich die Website mit ihren **Funktionen inklusive der Größenempfehlung** genau an.

Onlineshop Sewy

Der Onlineshop Sewy gibt Ihnen eine Größenempfehlung an. (Bitte spielen Sie das Video ab)

8.2 Größenempfehlung allgemein

Haben Sie bereits eine Größenempfehlung bei einem früheren Online-Kauf erhalten?

(Pflichtfrage)

- Ja
- Nein

8.3 Größenempfehlung Sewy

Hätten Sie im Onlineshop Sewy den Artikel in einer Nummer Größer bestellt?

(Pflichtfrage)

Sehr wahrscheinlich ○ ○ ○ ○ ○ Sehr unwahrscheinlich

Wie viele Varianten (Größe/Farbe) des Artikels im Onlineshop Sewy würden Sie bestellen?

(Pflichtfrage)

- Einen Artikel, da ich mir sicher wäre, welche Variante (Größe/Farbe) des Produkts ich kaufen würde.
- Zwei oder mehr Varianten des Artikels, da ich noch unentschlossen wäre.

Wie wahrscheinlich ist es, dass Sie nach der Bestellung des Artikels/der Artikel im Onlineshop Sewy retournieren würden?

(Pflichtfrage)

Sehr wahrscheinlich ○ ○ ○ ○ ○ Sehr unwahrscheinlich

9 Endseite

Es ist geschafft! Vielen Dank für Ihre Teilnahme!

Möchten Sie mir noch etwas mitteilen? Dann senden Sie mir gerne eine E-mail an s_basak18@stud.hwr-berlin.de

Appendix II: Further descriptive insights

*Gender * OnlineShopFreq Crosstabulation*

			OnlineShopFreq				
			Mehrmals im Monat	Etwa einmal im Monat	Etwa einmal alle drei Monate	Etwa einmal alle sechs Monate	Total
Gender	Weiblich	Count	10	19	31	19	79
		Expected Count	8,5	19,8	33,9	16,9	79,0
		% within OnlineShopFreq	12,7%	24,1%	39,2%	24,1%	100,0%
	Männlich	Count	2	9	17	4	32
		Expected Count	3,4	8,0	13,7	6,9	32,0
		% within OnlineShopFreq	6,3%	28,1%	53,1%	12,5%	100,0%
	Divers	Count	0	0	0	1	1
		Expected Count	,1	,3	,4	,2	1,0
		% within OnlineShopFreq	0,0%	0,0%	0,0%	100,0%	100,0%
Total		Count	12	28	48	24	112
		Expected Count	12,0	28,0	48,0	24,0	112,0
		% within OnlineShopFreq	10,7%	25,0%	42,9%	21,4%	100,0%

*Gender * ProdRetFreq Crosstabulation*

			ProdRetFreq		
			Ich retourniere regelmäßig online bestellte Bekleidungsartikel (bei jeder oder jeder zweiten Bestellung).	Gelegentlich retourniere ich online bestellte Bekleidungsartikel (bei jeder dritten Bestellung oder seltener).	Total
Gender	Weiblich	Count	28	51	79
		Expected Count	24,0	55,0	79,0
		% within ProdRetFreq	35,4%	64,6%	100,0%
	Männlich	Count	6	26	32
		Expected Count	9,7	22,3	32,0
		% within ProdRetFreq	18,8%	81,3%	100,0%
	Divers	Count	0	1	1
		Expected Count	,3	,7	1,0
		% within ProdRetFreq	0,0%	100,0%	100,0%
Total		Count	34	78	112
		Expected Count	34,0	78,0	112,0
		% within ProdRetFreq	30,4%	69,6%	100,0%

*Group*AI&Co. Trust*

	Group	N	Mean	Std. Deviation	Std. Error Mean
AI&Co.Trust	Interactive Group	39	1,77	,842	,135
	Non-interactive Group	31	2,03	1,016	,182

*SustainConsc * SustAware Crosstabulation*

			SustaAware			
			Ja, ich weiß, was mit den retournierten Artikeln geschieht.	Ich habe eine grobe Vorstellung, weiß aber nicht im Detail, was mit den retournierten Artikeln geschieht.	Nein, ich habe keine genaue Vorstellung davon, was mit den retournierten Artikeln geschieht.	Total
Susta-Consc (1=Sehr wichtig – 5=Sehr unwichtig)	Skalenoption 1	Count	7	8	2	17
		Expected Count	3,3	9,4	4,3	17,0
		% within SustaConsc	41,2%	47,1%	11,8%	100,0%
	Skalenoption 2	Count	10	20	7	37
		Expected Count	7,3	20,5	9,3	37,0
		% within SustaConsc	27,0%	54,1%	18,9%	100,0%
	Skalenoption 3	Count	4	25	11	40
		Expected Count	7,9	22,1	10,0	40,0
		% within SustaConsc	10,0%	62,5%	27,5%	100,0%
	Skalenoption 4	Count	1	8	4	13
		Expected Count	2,6	7,2	3,3	13,0
		% within SustaConsc	7,7%	61,5%	30,8%	100,0%
	Skalenoption 5	Count	0	1	4	5
		Expected Count	1,0	2,8	1,3	5,0
		% within SustaConsc	0,0%	20,0%	80,0%	100,0%
Total		Count	22	62	28	112
		Expected Count	22,0	62,0	28,0	112,0
		% within SustaConsc	19,6%	55,4%	25,0%	100,0%

Sworn declaration

I hereby formally declare that I have written the submitted Master's thesis entirely by myself without anyone else's assistance. Where I have drawn on literature or other sources, either in direct quotes, or in paraphrasing such material, I have referenced the original author or authors and the source in which it appeared.

I am aware that the use of quotations, or of close paraphrasing, from books, magazines, newspapers, the internet or other sources, which are not marked as such, will be considered as an attempt at deception, and that the thesis will be graded as a fail. In the event that I have submitted the dissertation - either in whole or in part - for examination within the framework of another examination, I have informed the examiners and the board of examiners of this fact.

Berlin, 24.07.2023

Place, Date   Signature