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VIRTUAL TRY ON FEATURE IN ONLINE FASHION RETAIL: CLUSTER SEGMENTATION THROUGH K-MEANS CLUSTERING BASED ON PRELIMINARY INSIGHTS

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Abstract

Virtual Try-Ons have recently emerged as a new type of augmented reality application aiming at personalising the customer's online shopping experience and enabling the visualisation of unique value from the ownership of the product. As such, augmented reality has significantly impacted online fashion retail. The lack of sovereignty over personal data due to amplified data tracking represents an obstacle to the adoption of new technologies. This research explores how customers respond to virtual try-on features and analyses the trade-off between willingness to share personal data and the perceived added value to the shopping experience related to different types of products.

Keywords: K-Means; Clustering; VTO; Willingness; Usefulness; Comfortability; Cluster

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1. Introduction

In recent years, comprehensive investigations have been carried out into the realms of fashion e-commerce and technology integration. Innovation is necessary to participate in this competitive landscape. Therefore, brands started implementing new technologies such as Augmented Reality (AR). AR is a market-disrupting technology sweeping online businesses (Pillarisetty and Mishra 2022). It is expected to significantly alter customers' interaction with content by placing them in the centre of the ever-expanding virtual world (Hall and Takahashi 2017). AR alters how people perceive the physical environment and bridges the gap between online and in-person buying.

This thesis examines Virtual Try-Ons (VTOs), which is a subcategory of AR. VTOs have been widely adopted by fashion retailers, who use it to enhance the shopping experience and collect unique user data. The development of VTO technology has been aided by the popularity of filters on social media platforms like Snapchat, Instagram, and Messenger. These filters have improved the accuracy and realism of facial recognition, machine learning, and 3D modelling techniques, making VTO technology more effective and user-friendly (Kwiecień 2021).

The COVID-19 pandemic greatly impacted the e-commerce boom and increased the significance of online shopping. Retailers have been searching for ways to elevate the online shopping experience by offering higher levels of personalisation at every touchpoint of the customers' journey. They have adopted personalisation strategies by converting insights into recommendations tailored to customers' preferences. When executed well, personalisation aids in developing meaningful connections with customers and enables a more relevant and pleasing online shopping experience ("What's Working in AR & VR 2021 | WARC" 2022).

Customers' privacy concerns and perceptions of the e-commerce platforms' reputation influence the decision-making process for online purchases. Customers' concerns about privacy are generally negatively correlated with their attitudes towards VTOs and their corresponding purchase intentions with AR-based technologies (Eastlick, Lotz, and Warrington 2006). In response, companies active in e-commerce are employing data scientists to improve personalisation and gather insights into the data collected. Hence, these insights strongly depend on the customers' willingness to disclose personal information (Gouthier et al. 2022). However, the topic needs to be further explored to understand how privacy concerns change in different scenarios related to different types of products and VTOs.

The purpose of this thesis is to investigate customer responses towards VTO technology and their perceptions of the experience for different product types. Additionally, the study aims to determine whether there is a trade-off between the willingness to share personal data and the perceived value of the VTO experience for different types of products. Lastly, the study explores how preferences and perceptions differ across segments and identifies the ideal features of the VTO for eyewear.

To conduct this research, a preliminary survey was developed to gather insights on customer responses to VTO features. Five expert interviews were conducted to identify factors and attributes to evaluate customer perceptions. An exploratory data analysis and a perceptual map analysis were performed to gain an understanding of customers' perspectives and the positioning of the products. Furthermore, a brand-specific conjoint analysis was carried out to evaluate the potential trade-off between data sharing and the perceived added value of the VTO experience. A K-means cluster analysis was performed based on the results of the preliminary survey to create consumer segments for this market. Finally, a choice-based conjoint analysis was performed to determine the optimal experience for eyewear VTOs and provide recommendations for eyewear brands considering or offering a VTO experience to their customers.

In order to gain a greater understanding of this thesis, it is essential to provide a detailed overview of each chapter and its interconnections. Chapter 2 offers a background to the topic, with a discussion of AR technology and its application to the personalized online shopping market, the concept of VTO and its various features. It also addresses the issue of data privacy. Chapter 3 delves into the literature review. This chapter analyses previous research that has been conducted on the topic, providing insightful factors that need to be taken into consideration when studying consumer behaviour towards a VTO feature. This allowed for a topic narrowing and the identification of specific factors for perceptual mapping, attributes, and corresponding levels for conjoint analysis. Next, Chapter 4 summarises the main inputs gathered from expert interviews that allowed us to confirm the previously summarised insights from literature research. These interviews were conducted with technology and industry experts, providing perceptions from both sides. Chapter 5 analyses general insights from the preliminary survey and, alongside literature and expert interviews, provides a basis for the most relevant factors to test. At the same time, it allows for customer clusters, discussed in Chapter 8. Chapter 6 incorporates an exploratory general data analysis and an analysis of perceptual maps. Both allow for conclusions on customer perceptions of the feature according to different tested factors, the positioning of products and their associations with the same factors. The first general data analysis serves as a complementary study for the perceptual mapping and is included within the perceptual maps since it uses data from the same study, follows the same rationale of factors, and aims to answer the same questions. Chapter 7 explores customers' preferences through a brand-specific conjoint analysis that aims to focus the customers' attention on data sharing explicit needs, allowing for the interpretation of the trade-off between willingness to share data and the perceived added value of the online shopping experience.

Chapter 8 addresses the creation of cluster segments based on the data retrieved from the preliminary survey, focusing on the age demographic and behavioural data collected. Finally, Chapter 9 provides clear recommendations on the ideal features of the experience of virtually trying on eyewear, through a choice-specific conjoint analysis.

2. Background

The global fashion e-commerce market, which encompasses the sale of apparel, footwear, eyewear, bags, accessories, jewellery, and cosmetics through online channels, has seen significant growth in recent years. According to ReportLinker (2022), the market value reached nearly $700 billion in 2021 and is expected to surpass this number by the end of 2022, reaching over $1.2 trillion in 2025 (Alsop 2022). Clothing, accessories, and footwear account for the largest e-commerce sector worldwide, with a market value amounting to nearly $759.5 billion in 2021 (Orendorff 2021). Key factors contributing to this growth include globalisation, progress in digitalisation, and the increase in internet and smartphone usage. Additionally, the COVID-19 pandemic has created a conducive environment for the growth of e-commerce fashion marketplaces, as Berg et al. (2020) described as “a perfect storm".

The retail industry and the corresponding shopping experiences are changing due to the extensive usage of digital technologies (Caboni and Hagberg 2019). Advanced technologies with a higher degree of interactivity enhance the overall shopping experience and contribute to the customers’ willingness to purchase products. As a result, the point of sale becomes a new immersive place where digital technologies merge with traditional elements and enable a distinctly personalised and interactive atmosphere (Caboni and Hagberg 2019). Therefore, increasing all activities in the digital world where companies communicate and engage with clients in new ways is a crucial adaptation need (Berg, Stander, and Vaart 2020).

This thesis examines the use of Augmented Reality (AR) in e-commerce as a means of enhancing the online shopping experience. AR technology overlays virtual data or a virtual world on top of the real-world surroundings, augmenting the users' perception of their environment (Hayes 2020). It simply augments a world that exists and can still be perceived to some extent (BigCommerce 2022). AR is a technology that "combines real and virtual objects in a real environment, runs interactively and in real-time, and registers real and virtual objects with each other" (Azuma et al. 2006). It aims to provide tools that can help replace the lack of touch and feel in any online activity (Caboni and Hagberg 2019), while there is growing evidence that consumers benefit from AR in e-commerce (Hayes 2020).

VTO systems provide an experience that resembles trying on clothes similarly to when in a physical store, while reducing the perceived risk often associated with regular online shopping (Pillarisetty and Mishra 2022). The feature provides the capability of sensory and tactile evaluations (Beck and Crié 2018) and improves the customer experience in various ways. This technology displays items on the users' body and tracks their movements through the device's camera. By creating a more interactive way of shopping, VTOs increase the entertainment correlated to the online shopping experience (Kim and Forsythe 2008). Customers can now try on a product before purchasing it from any location, having the benefit of being in the comfort of their homes without feeling the pressure of sales assistants (Schell 2021). Additionally, customers can sense interaction with actual products, visualising the fit with their accessories while also being able to consult with friends. Consecutively, they can enjoy a personalised shopping experience and save time (Kwiecień 2021).

In order to create vivid experiences for customers, the usage of digital technologies has been rising. VTOs can further be differentiated into distinctive forms. For the purpose of our research, two types of technology were examined, namely (i) Avatar VTOs and (ii) Self-recording

VTOs. These provide a more personalised and engaging shopping experience for customers while also providing retailers with unique user data and insights. A consideration of Virtual Mirror VTOs has been included in our study, although it is not subject to a more detailed analysis. These technologies are changing how the fashion industry operates and providing new opportunities for retailers and designers to connect with customers.

Virtual avatars are becoming increasingly popular in the retail industry, as they provide a higher level of image interactivity and enable customers to see themselves in different bodies (Genay, Anatole and Hachet 2022). Virtual avatar technology, as described by Lee, Fiore, and Kim (2006), allows the consumer to choose from a range of avatars with different genders, body shapes, and heights. With the use of this technology, users can experiment a variety of front and rear texture-mapped product image combinations. Customers can utilise technologies such as body scanners to quickly and accurately generate 3D representations of themselves, allowing them to virtually try on apparel and accessories to visualise how they would look on their bodies. One company that is pioneering the use of virtual avatars in the retail industry is Drapr, a 3D avatar and e-commerce start-up recently acquired by GAP Inc. Drapr's technology allows customers to create 3D avatars of themselves and try on clothing in a virtual environment, providing a unique and engaging shopping experience (Grothaus 2021).

Self-recording VTO are a type of VTO technology that uses a video or picture of the user to show how clothes and accessories would look on them. This technology allows customers to record themselves on a camera-equipped device, such as a smartphone or laptop, and see a realistic virtual representation of the product overlaid on their live video. It further provides a more personalised and engaging shopping experience, as customers can see how the product would look on their own bodies (Retter 2022).

The implementation of such a VTO feature in the online shopping experience is most common for eyewear and has been implemented by several brands (e.g., Ray-Ban, Zenni Optical, Mister Spex, Quay Australia, Michael Kors). Eyewear brand like Zenni Optical and Quay Australia have implemented self-recording VTOs to enhance customers' online shopping experience. Customers can obtain product recommendations by recording themselves on the video, which leads to a 3D 180-degree scan of the face. More accurate sizing and fitting recommendations can be obtained by sharing the pupillarity distance or using a (credit) card as a measurement tool by placing it on the forehead (Zenni Optical 2019; Quay Australia 2022). Another example of a VTO application in the eyewear category is Michael Kors, which used Facebook to allow consumers to try on sunglasses through the app virtually.

Brands like Body Labs and 3DLOOK have created blended reality systems that allow customers to visualise themselves wearing a specific product in a virtual setting. 3DLOOK introduced the “YourFit” app that integrates AR clothing try-on with size and fit suggestions (3DLOOK 2022). While there are few applications of the VTO feature in the apparel category, several fashion brands have tested Snapchat's apparel try-on tool. An example of this is Farfetch with Virgil Abloh's Off-White collection, which enabled users to virtually try on a jacket that they could buy directly through Snapchat. In addition, some fashion clothing brands (e.g., Prada, Farfetch) have implemented the VTO feature as a social media filter on Snapchat. Correspondingly, Prada tested the hands-free VTO, where users could virtually try on clothing and change product colours by using swiping hand gestures (Farfetch 2022; Prada 2022).

Technological improvements in AR-based augmentation for footwear enabled the application of the VTO feature in the shopping experience of various fashion brands (e.g., Nike, Gucci, Farfetch, Converse). Nike's “Nike Fit” app uses self-recording VTOs to provide sizing recommendations by scanning the customers’ feet and allowing them to visualise the product as if they were trying it on in real life. Gucci has also implemented VTO technology in their app to allow customers to try on their Ace sneakers line virtually (Kwiecień 2021).

Virtual mirrors are a type of technology that simulates a mirror by showing the user's image on a screen. These virtual mirrors act as virtual fitting rooms and use a combination of radio frequency identification (RFID) technology and augmented reality (AR) technology to allow users to try on clothing and accessories in a virtual environment. Once the customer brings a piece of clothing in front of the virtual mirror, it scans and records the image of the item. The mirror then creates a virtual representation of the user wearing the item and displays it on the screen. The virtual clothing can be adjusted to the user's size and shape in real-time, providing a highly personalised and engaging experience. Virtual mirrors have been used by retailers such as H&M. H&M uses virtual mirrors in selected COS stores to track which products customers bring into the fitting rooms and offer personalised products and styling advice (Nishimura 2022).

Overall, these different types of VTOs provide unique and engaging experiences for consumers, allowing them to try on clothes and accessories without having to physically visit a store. This can be particularly useful for online retailers, as it allows customers to make more informed purchasing decisions and can help to increase customer satisfaction and loyalty.

3. Literature Review

This chapter presented a deeper understanding of the relevance of the topic, ensuring the accuracy of the variables used in both perceptual maps analysis and conjoint analysis, as well as highlighting the importance of a post-hoc segmentation for our study. Not only it brought relevant insights of this new market, it also led the group's choice of the three elected product types: upper garments, eyewear, and footwear.

4. Preliminary Interviews: Experts

This chapter worked has a base for insights for our further analysis, looking for different expert perspectives of the VTOs in the online fashion retail industry. The group interviwed 5 different experts, in the field of technology and fashion.

5. Preliminary Survey: General Insights

5.1. Methodoly

A preliminary survey, developed in Microsoft Forms, collected a total of 228 respondents and was the basis of the general insights analysis.

5.2. Results

Sample characteristics

The following results are based on a sample of 228 respondents. Of these 228 respondents, 61% are female, 38% are male, and one preferred not to specify their gender. When considering age distribution, the majority of sample is found to be between 17 and 25 years old, accounting for 53% of respondents, followed by the age group of 26 to 35, with 19%, then by 46+, with 15%, and 36 to 45, with 14% (See Appendix 12.3.2, Figures 13 and 14). As for the income level of the sample, the results do not seem relevant for the present research since 28,9% of the sample chose the option *“Prefer not to say”*. Nevertheless, most of the respondents who revealed the total annual household income (before tax and deductions but including any benefits/allowance) have an income level *“Bellow 10,000€”*, representing 19,2% of the sample. This result might be related to the high percentage of young respondents that belong to the age group 17 to 25 years old. This income level is followed by *“Above 50,001€”*, accounting for 17,9% of the sample. (See Appendix 12.3.2, Figure 15).

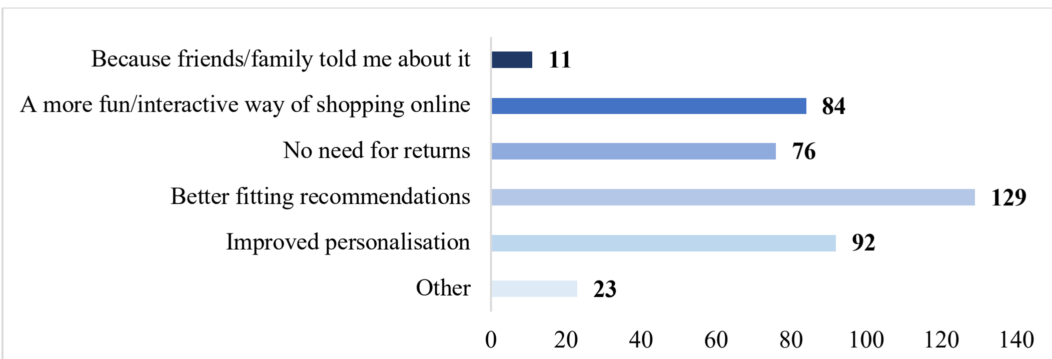
When analysing the sample’s online shopping frequency, the most common frequency is *“Monthly”*, accounting for 30,2% of the sample. Next in line is *“Occasionally”*, with 25,4%, followed by *“Seasonally”*, with 23,6%. *“Weekly”*, *“Never”*, *“Yearly”* and *“Daily”* were the least chosen options accounting for 7%, 6,6%, 5,7% and 1,3%, respectively (See Appendix 12.3.2, Figure 16). These results allow for a great analysis of potential new customers for the online fashion retail industry, if they consider that VTOs can bring more benefits to their experience, as well as understand the main problems identified by the already regular online shopping consumers.

Finally, when asked about the type of fashion products the respondents buy online, and allowing for the possibility of choosing one or more options, *“Top clothing/upper garments”* was the main chosen option, with 181 clicks. This is followed by *“Bottom clothing”* (139 clicks), *“Footwear”* (122 clicks), *“Accessories, including jewellery, handbags, etc.”* (105 clicks), *“Underwear/swimwear”* (80 clicks), *“Eyewear”* (55 clicks), *“None”* (19 clicks) and *“Other”* (4 clicks). These results show the high presence of upper garments and footwear in the online fashion industry and some relevance of eyewear in the same industry (See Appendix 12.3.2, Figure 17).

Preliminary Survey Results

When analysing the results conducted from the survey to gather more information about digital transformation through augmented reality in online fashion retail, we conducted 228 responses. In the first question, 74% (168 respondents) implied they had never used a feature such as a VTO before. The other 36% of the answers stated to have used a VTO before. Most of this percentage used it occasionally, divided into three smaller groups dedicated to: sometimes, seasonally, or often. However, 53,5% of respondents indicated they would consider using a VTO to improve their online shopping experience in the future, and 32,9% of respondents answered *"Maybe"*. The last part is dedicated to 13,6% of respondents who would not consider using the VTO in the future. The main reasons to shop online are presented below in Figure 1. Many respondents chose *"Better fitting recommendations"* (129 clicks), *"Improved personalisation"* (92 clicks), and a *"More fun and interactive way to shop online"* (84 clicks).

Figure 1: What are the main reasons for using a virtual try-on when shopping online? (Choose 1 or more options)



The results generated in our survey show that 55% of respondents see additional value in brands or fashion retailers that offer a VTO feature. Many of this group of respondents prefer to use the feature on the brand's website or app. This group consists of 87% of the 55%. Next, we evaluate the causes that restrain respondents from using the VTO feature. The biggest group consists of *"Data privacy concerns"* (79 clicks). Other reasons are the *"Lack of human interaction"* (49 clicks), and *"Bad quality recommendations"* (48 clicks). However, (21) respondents mentioned that something else was holding them back from participating in a VTO.

The overall usefulness of a VTO feature for finalizing a purchase will be further explored in the Cluster Analysis, Chapter 8. Chapter 8. Additionally, respondents had to fill in the likelihood of sharing their measurements, uploading a photo of themselves, or recording a part of their body to a platform using the VTO feature. The respondents were *"Very likely"* to share their measurements. In contrast to when the respondents have answered the likeliness to record themselves (77) respondents answered, *"Very unlikely"* (See Appendix 12.3.2, Figure 21).

The extent of distrust in how data will be processed is stopping respondents from using a VTO feature, resulted in an average rating of 3.31 on a scale from 1-5, where 45% rated between the 4 and 5 (See Appendix 12.3.2, Figure 28) This will be discussed thoroughly in Chapter 8. Next, we analysed for what products the respondents were more likely to accept the data privacy terms and conditions without carefully analysing them. The results show that *"Footwear"* (138) and *"Eyewear"* (90) are products where the respondents are more likely to accept privacy terms and conditions without further research. *"Upper garments"* collected (69) answers, and the option *"None"* was selected (39) times (See Appendix 12.3.2, Figure 30).

The survey also had the intuition of gathering information related to the different types of products the group chose to explore: (i) upper garments, (ii) footwear, and (iii) eyewear. In this sense, the respondents were asked to rank the three types of products, according to *"Willingness"* and *"Usefulness"* to virtually try them on. When considering willingness, footwear is the first choice of respondents. This conclusion is drawn given that although eyewear was chosen more times as a first choice, footwear is very close to the same result, and on top of that, it was the least chosen segment as the last choice. Upper garments were mostly chosen as a second and third options. The latter represents the majority of choice of respondents for upper garments. This means that the following order represents willingness to virtually try on these products: (i) footwear (ii) eyewear and (iii) upper garments (see Appendix 12.3.2, Figure 31). As for usefulness, eyewear was chosen as the first option for most of the respondents, followed by upper garments, and, finally, footwear, which also represents the majority of the last choice of the respondents (see Appendix 12.3.2, Figure 32).

As for comfortability in virtually trying on the different types of products, the respondents show different levels of comfort according to the different body parts they would be required to share. The overall analysis of results shows that respondents are the most comfortable with virtually trying on shoes; 48% of the respondents chose *"Very comfortable"*, when asked *"How comfortable would you feel to virtually try-on shoes?"*. Eyewear is the segment that follows, gathering 38% of *"Very comfortable"* respondents, and upper garments are the product for which respondents seem to be less comfortable with virtually trying on, knowing that the most chosen option was *"Somewhat comfortable"*, with 29% of respondents. Nevertheless, these results show great potential for the three products in the universe of VTOs since most respondents seem comfortable engaging with this feature (see Appendix 12.3.2, Figures 33 to 35). These questions of the survey will also be further explored in Chapter 8. When asked if virtually trying on the different products would help the respondents to decide more easily when shopping online, the results, as expected, were similar when asked about the ranking of products by the usefulness of the VTO. In this sense, the majority of respondents answered *"Yes"* for upper garments (44%) and eyewear (62%), and the majority of respondents answered *"Maybe"* for footwear (37%). Still, 32% of the respondents answered *"Yes"* for the footwear segment (See Appendix 12.3.2, Figures 36 to 38).

This survey highlights the great availability for customers to interact with this technology, although the majority of them has never tried a VTO before. It is fundamental to understand which features would allow for greater willingness to interact and which product category would suit this new market better.

6. Perceptual Maps

This chapter analyzed customers' perceptions of Virtual Try-On (VTO) features for different products, using exploratory data analysis and perceptual map analysis. The focus of the study is on the perceptions of the perceived added value and data privacy concerns of virtually trying on different products. A complex multidimensional perceptual map, displays all the products and analyzed factors in the same map and focuses on patterns between them.

7. Conjoint Analysis

The previous chapter explores customers' responses to VTOs, by analysing their willingness to use the feature and disclose personal data along with their perceptions about its usefulness, quality of recommendations, user-friendliness, and interactivity. This chapter addresses privacy concerns to understand the relationship between customers' willingness to share data and the perceived added value of using a VTO feature. By enabling individuals to choose between different privacy settings that, in exchange, offer different online shopping experiences, we evaluated the level of personalisation that makes individuals risk disclosure of personal data to benefit from a more personalised experience. Firstly, the chapter presents the methodology behind the choice of attributes and respective levels. The methodology is followed by the analysis of the results, which are divided into two sections: the analysis of the sample and the analysis of segments derived from the original sample.

7.1. Methodology

Attributes and Levels

The group identified a gap in the literature regarding customers' willingness to disclose personal data to obtain a personalised online shopping experience. There is a knowledge gap on how these changes relate to different product types. Taking that into consideration, the main goal of our conjoint analysis was to research the direct trade-off between the detailed data the customers needed to share to take advantage of the different types of online shopping experiences.

The participants were presented with data privacy concerns in the previous analysed surveys, although the focus was not directly related to this concern. However, in this survey, the respondents faced a more conscious choice when discussing data sharing.

As mentioned before, the choices of attributes were related to the literature review and the conducted expert interviews, not only in the technology industry but also in the fashion industry. Our final decision included three attributes: (i) *"Product Type"*, (ii) *"Online Shopping Experience"*, and (iii) *"Data Privacy"*. The group acknowledged that attributes (ii) and (iii) are endogenous variables, as it is only possible to provide an online shopping experience by having to share the related data. In this case, we faced simultaneity between variables, knowing that not only does the variable *"Data privacy concerns"* causes the variable *"Online shopping experience"*, but the opposite is also happening (Glen 2020). Nevertheless, the choice of keeping them separate in the conjoint survey was made because it would be the only way to examine and answer our research question. We were able to make further conclusions on the research topic by presenting the respondents with the specific data necessary to share to provide a personalised online shopping experience. This could only be taken into account if each potential online shopping experience was linked to an attribute that, at each level, required increasing data-sharing steps as personalisation increased.

The chosen attributes and corresponding levels passed through different reviewing stages. The first attempt survey was sent to a smaller sample of respondents to ensure comprehension and good respondent friendliness. Some suggestions were accepted, such as the inclusion of images to make the online shopping experiences more visual, assuring more respondent attention while filling out the survey. After this first revision stage, the survey was then shared with the thesis advisor and with this feedback, the group formulated the final survey design. The final survey provided clear instructions for the respondents to be aware of the different types of online shopping experiences, generating awareness which would lead to making informed decisions.

Due to the identified gaps in the literature review (See Appendix 12.4.1, Table 19) on the comprehension of consumer behaviour towards different types of products, we included the first attribute, namely, *"Product Type"*. Further research on this topic would be beneficial for the online fashion retail industry. With the insights from expert interviews, we established that some products might be more relevant than others when focusing on a VTO experience. The highlighted product types (levels) were chosen due to their relevancy in the current market, and their market potential. The literature review showed the significance of (i) *"Eyewear"* in this industry due to the diversity of brands that already offer this service and also because it is perceived as one of the market segments with more utility for customers. (ii) *"Footwear"* was chosen for the same reason as eyewear; various brands offer this service, and this segment seems to have great potential, according to the literature. The last product, (iii) *"Upper Garments"*, was chosen due to the necessity of including different body parts to have the possibility to explore consumer sensitivity according to what would need to be shared with the application/website. Insights from a VTO technology expert predict that this segment will have great potential in the future of VTOs in online fashion retail.

The second attribute, *"Online Shopping Experience"*, was chosen as it allows participants to compare online shopping options, leading to conclusions on customers' response towards the usage of VTOs. The levels were selected with the above considerations in mind and the literature review, namely: (i) *"Regular online shopping"*, (ii) *"Personalised online shopping through shared measurements"*, (iii) *"Personalised online shopping with an avatar"*, and (iv) *"Personalised* *online shopping with VTO"*, using the user's body image as these were the leading online shopping experiences from previous research analysis.

Customers are required to accept certain data-sharing settings to obtain the full personalised experience on online fashion platforms. These data-sharing settings commonly include mandatory cookies, which need to be accepted to obtain the benefits of platform functionality and better site navigation. Customers are presented with the option of only accepting some cookies, such as personalisation of cookies, which enables platforms to track when the customer visited the site and provide customised advertisements on other sites (Stradivarius 2022). According to Zara (2022), Fit Analytics, higher personalisation in terms of product recommendations based on shared body measurements, requests access to the following: customer fit profile, fit finder user ID, the shop user ID, the purchase and return data, event data and technical data (browser type and version, operating system, device name, IP address). Essential cookies store customer's fit finder preference for 360 days, while non-essential cookies store customer information for 90 days, allowing the platform to generate recommendations or advertising services and general analytics. (Zara 2022).

VTOs are categorised as a higher-level personalised online shopping experience that requires a higher amount of data disclosure. According to platforms using VTO features, customers using a VTO feature are required to grant access to their device's camera and consent to capturing and storage of personal images. Using cookies, the platform collects personal data, including a body scan, birthdate, gender, device identifier information, IP address, date, and time stamp of the session. (Quay Australia, 2022; Farfetch 2022).

The last attribute, *"Data Privacy"*, was chosen considering the user's privacy concerns and the need to evaluate the trade-off between willingness to share data in exchange for the perceived added value to the user's online shopping experience, as explored in Chapter 3. This attribute is entirely related to the user's online shopping experience preference. Therefore, they turn into one single attribute presented separately in the survey to increase users' awareness of data sharing related to the different online shopping possibilities. The levels were selected accordingly to assure that the respondents would make conscious choices regarding their data privacy concerns and perceived added value. The relationship between *"Online Shopping Experience"* and *"Data Privacy"* can be found in Table 8, presented below.

Table 1: Endogenous Variables and correspondents

Experience	Online Shopping Experience	Data Privacy
1	Regular Online Shopping	Accept mandatory cookies
2	Personalised online shopping based on shared measurements	Accept mandatory cookies, share personal measurements
3	Personalised online shopping with an avatar	Accept mandatory cookies, share personal measurements, upload a picture
4	Personalised Online Shopping with Virtual Try-On	Accept mandatory cookies, terms & conditions VTO, give access to camera

In the conjoint analysis survey, the order of attributes was chosen as follows: (i) *"Product Type"*, (ii) *"Data Privacy"*, and (iii) *"Online Shopping Experience"*. This order was consciously chosen considering the customer's journey. The first step is the need to buy a product, therefore, the product comes first. Secondly, the group chose *"Data Privacy"*, in order to focus the respondent's attention on his/her concerns. Lastly, with data privacy concerns in mind, the most suitable *"Online Shopping Experience"* for the customers is presented to them.

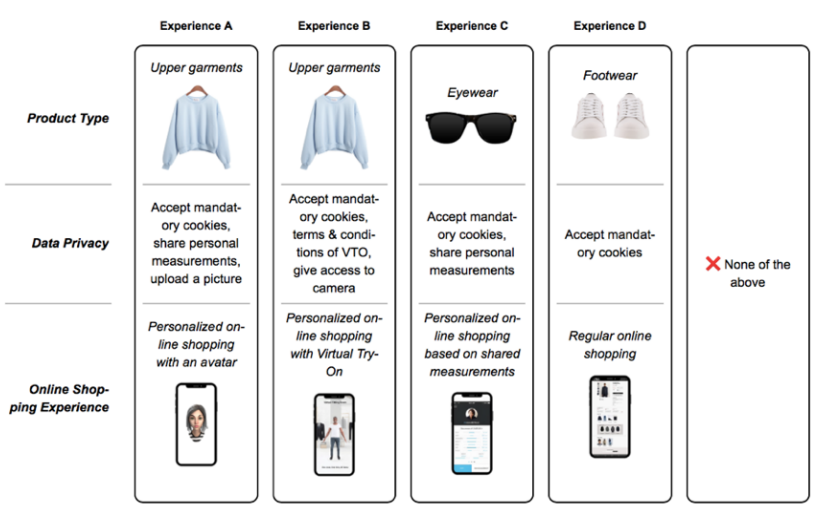
Initial Survey Setup: Conjoint.ly

As stated before, as part of the review stage, the survey was sent to a smaller sample of respondents, and we received positive feedback about the survey being intuitive and easy to follow.

Conjoint.ly was the chosen platform due to the ease of use for both the group and respondents' perceptions. This platform provides advanced tools that are beneficial for a deeper conjoint analysis. For our study, a brand-specific conjoint was selected. The choice-specific conjoint would only allow for limited restrictions, and we wanted to have the possibility of selecting all the correct combinations of attributes and levels. Since *"Online Shopping Experience"* and *"Data Privacy"* are endogenous variables, several restrictions within these two attributes needed to be made (See Appendix 12.4.1, Table 20).

The survey layout consisted of three sections: (i) the introduction, where the group explained how the survey would work, and the different online shopping experiences were presented. (ii) the choices were generated randomly according to the necessary restrictions the group selected, and (iii) three additional questions to gather information from the characteristics of the sample, including gender and age, and an opened ended question to get insights from the consumer's perspective about VTOs. An overview of the survey design can be found in Appendix 12.4.1, Figure 62. Regarding the design of the survey, an option allowing the respondent to choose none of the presented experiences was made available. The number of choices of different online shopping experiences presented at the same time was set to four, allowing the chosen four levels to appear simultaneously. Each respondent was required to make 12 choices. In *"Product Type"* and *"Online Shopping Experience"* the group chose correspondent images to each level, creating a more realistic experience. An overview of the survey layout is found in Figure 7, below.

Figure 1: Layout of the choice sets within Conjoint.ly



Pre-Test and Data Collection

As mentioned in this chapter, a pre-test of the survey was made with a small sample of respondents to assure clarity and respondent friendliness. After receiving the feedback, some changes were made, such as the inclusion of images in *"Product type"* and *"Online shopping experience"*. The survey was open from October 11th, 2022, to October 22nd, 2022. The distribution channels used were the group members' social media accounts (Instagram, Facebook, LinkedIn), and family and friends' social media groups (Messenger, WhatsApp, Email). To gather more responses, the group distributed the survey to different research groups on Facebook and other websites, such as Survey Circle.

7.2. Results

Sample Characteristics

This analysis was based on 130 responses, and the group focused on two demographics: age and gender. The sample is divided into 65,1% women, 34,1% men, and 0,8% who preferred not to specify their gender. The majority of the sample (71,4%) belongs to the age group between 17 and 25 years old, followed by 16,7% of respondents between 26 and 35, 4,8% between 36 to 45, and 7,1% with 46 years or more years old (See Appendix 12.4.2, Figures 63 and 64).

Conjoint Analysis Results

The analysis presented below was based on the report provided by the Conjoint.ly software, and it includes the preferred data privacy settings, the respective online shopping experience preference, and the relevance per attribute and levels. The data was based on all responses of the sample, which were considered as good to include in the analysis by the same software, as well as the responses from the age segments that we created, to identify differences of availability to engage with the feature in exchange for more data sharing.

General Analysis

<u>*Data Privacy/Online Shopping Experience Preference*</u>

The output given by Conjoint.ly encompasses the preferred online shopping experience given the preference for data sharing. Considering that, and through the analysis of Figure 8, one can derive the data shown in Table 9, presented below. The figure reflects the medians for each data privacy/online shopping experience through the diamonds presented on each violin. The violins represent the estimated distribution of data, considering minimums and maximums. The highest median is found in *"Accept mandatory cookies"*, valued at 7,5, meaning the online shopping experience customers prefer the most would be *"Regular online shopping"* (1). This experience is followed by *"Personalised online shopping through shared measurements"* (2), with a median of 6,9. These two experiences are the only ones that present a positive median value, meaning they are the most preferred by the respondents. Although the medians are very close, *"Personalised online shopping through shared measurements"* (2) encompasses customers on the far left that show lower preference for this experience, as when compared to the minimum and maximum value of *"Regular online shopping"* (1), where the distance from the median is smaller both in the far left and far right, resulting in higher preference for regular online shopping (1).

Figure 2: Data Privacy/Online Shopping Experience Preference (based on average responses)

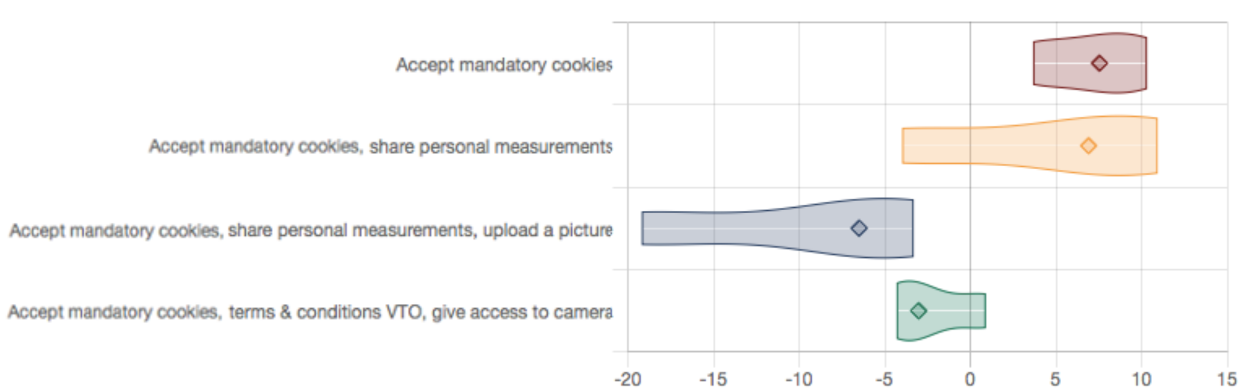


Table 2: Data Privacy/Online Shopping Experience Preference Descriptive Statistics

Data Privacy/Online Shopping Experience	Minimum	Median	Maximum
1	3,7	7,5	10,3
2	(3,9)	6,9	10,9
3	(19,2)	(6,5)	(3,3)
4	(4,3)	(3)	0,9

<u>*Ranked list of concepts/Product Preference*</u>

Aiming towards the objective of understanding consumer behaviour towards different types of products, we focused on three product types: (i) eyewear, (ii) footwear and (iii) upper garments. From our analysis, the highest value perceived for VTO usage was for the upper garment product category.

More specifically, the options shown in Appendix 12.4.2, Table 21 serve as a list of every potential combination shown to respondents and sorted by their top choice profiles. There are 12 rankings in total that indicate the added value to the customer's experience. The top 3 rankings were examined as they are comprised of positive values, which would inherently serve the objective of our study in exploring the added value of VTOs, used in specific product categories, for the customer's online shopping experience. The rating is based on the relative effectiveness of the combined levels, which enables customers to identify the best choice they favour above other alternatives. In order to get a more personalised online shopping experience with shared measurements, it was discovered that many individuals were willing to use VTOs for upper garments while accepting mandatory cookies and sharing personal measurements. This was also ranked in first place with a median of 10,9, according to respondents' preferences. Footwear was ranked second with a median value of 10,3, accompanied by a regular online shopping experience, where the customer would have to accept only the mandatory cookies. The third highest ranked product category was, once again, upper garments. However, in this case, the customer would have to accept mandatory cookies only to obtain a regular online shopping experience with a median of

7,5. The last preferred experience was ranked sixth, in the product category of upper garments with a median of 0,9, where the customer would have to accept mandatory cookies, terms & conditions for VTOs and give access to their device's camera in order to have a more personalised online shopping experience with a VTO feature.

<u>*Attribute Importance*</u>

As stated before, the developed conjoint analysis encompasses two different attributes that count as one single attribute, corresponding to *"Data Privacy/Online Shopping Experience"* since they are endogenous variables. As these attributes are related to the *"brand preference"* part of the Conjoint.ly report, it is expected that only one attribute will be left and that its relative importance accounts for 100%. In this sense, *"Product Type"* has a total influence on the choice of customers, allowing for a deeper understanding and responding to the question of how the product type influences consumer behaviour, hence bridging the gap identified in the literature review.

<u>*Relative Importance by Level*</u>

The level partworths are calculated relatively, meaning that the inclusion of another level in the *"Product Type"* attribute would influence the percentages presented in Table 10, shown below. These same values are retrieved based on the average preferences of the sample respondents, knowing that the highest values correspond to the highest preferences. In this sense, the negative values correspond to the lowest preferred experiences, and the sum of all positive values should be equal to the sum of all the negative values.

Table 3: Partworth utilities of all the experiences – Product Type

Attribute	Levels	Experience 1	Experience 2	Experience 3	Experience 4	Average across experiences
Product Type	**Upper garments**	5,6%	**42,3%**	**40,0%**	**58,5%**	36,6%
	Footwear	**47,2%**	15,4%	(60,0%)	(17,1%)	(3,6%)
	Eyewear	(52,8%)	(57,7%)	20,0%	(41,4%)	(33,0%)

When looking at the average across experiences in Table 10, it is noticeable that upper garments are the highest preference of the respondents. This happens because it is the only positive value (36,6%), which is followed by footwear (-3,6%) and eyewear (-33%). This shows that eyewear and footwear, which present negative values, are less preferred products for all online shopping experiences on average, and eyewear holds the place explicitly for the least preferred level. Nevertheless, it is crucial to analyse which experience the customers would be more likely to engage in, given their preference for upper garments. Table 10 shows that *"Personalised online shopping with VTO"* (4) is the experience for which the customers seem to have higher preferences for this level (58,5%).

It is now important to understand customers' preferences for "*Online Shopping Experience*" per "*Product Type*" in more detail. As already mentioned, upper garments is the most preferred level, and the optimal experience for this segment, according to the sample's data, would be the VTO. In contrast, the least optimal experience for this level would be *"Regular online shopping"* (1) (5,6%), associated with "*Accept mandatory cookies*". When analysing the second level, footwear, the optimal online shopping experience for the sample would be *"Regular online shopping"* (1) (47,2%). The reasoning might be explained by the fact that customers do not perceive so much added value in increased personalisation for this segment, as explored in Chapter 5. In contrast, the least optimal online shopping experience for this segment would be avatar, experience 3, (-60%), which also reflects the same reasoning of the optimal experience. Finally, concerning eyewear, the optimal experience for this level is avatar, experience 3, (20%), associated with "*Accept mandatory cookies, share personal measurements, and upload a picture*". In contrast, the least optimal is personalised online shopping based on shared measurements, experience 2, (-57,7%), associated with "*Accept mandatory cookies, and share personal measurements*". This analysis gives insights into the optimal and less optimal online shopping experience, considering all experiences and levels, for the sample's respondents, and the summary of these conclusions are presented in the following Table 11.

Table 4: Optimal experience for each level

	Product Type Levels		
	Upper garments	**Footwear**	**Eyewear**
Optimal	Experience 4	Experience 1	Experience 3
Least optimal	Experience 1	Experience 3	Experience 2

It is now essential to focus on the ideal product type for each experience. Looking at Table 11, one can infer the conclusions presented on Table 12 below. For "*Regular online shopping*" (1), the optimal product is footwear (47,2%), while the least optimal is eyewear (-52,8%). For *"Personalised online shopping through shared measurements"* (2), the optimal product is upper garments (42,3%), while the least optimal is eyewear (-57,7%). For *"Personalised online shopping through avatar"* (3), the optimal product would also be upper garments (40,0%), and the least optimal is footwear (-60,0%). Finally, for *"Personalised online shopping through VTO"* (4), the optimal product would also be upper garments (58,5%), while the least optimal is eyewear (-41,4%). This shows the relevance of upper garments for all experiences, except for the first one, meaning more personalisation is extremely valued for this market segment. In contrast, eyewear is not favoured in any personalised online shopping experience or in regular online shopping.

Table 5: Optimal level for each experience

	Experience Levels			
	1	**2**	**3**	**4**
Optimal	Footwear	Upper garments	Upper garments	Upper garments
Least optimal	Eyewear	Eyewear	Footwear	Eyewear

Segment Analysis

Data Privacy/Online Shopping Experience Preference

When analysing *"Data Privacy/Online Shopping Experience"* preference, it is clear that the behaviours per segment differ (see Appendix 12.4.2, Table 22). Although *"Regular online shopping"* (1) is the highest preference for the age group between 17 and 25 years old, one can infer that the major influence for this experience to be the highest preferred is the age group between 36 and 45 years old, knowing that their minimum (14,6) is higher than the maximum of every other age group for this experience. In contrast, the age group between 26 and 35 years old is the one that influences the median of the whole sample to decrease, knowing that the median of this age group is 3,7, with a minimum of -2,0.

By analysing the data per segment for *"Personalised online shopping through shared measurements"* (2), it is noticeable that the age group with 46 or more years old is the one that influences the increase of the all-sample median. However, all the other age groups also seem to perceive this experience as positive, meaning it is also part of the most preferences for all age groups, alongside regular online shopping (1). In contrast, the age group that pushes this median down is the age group between 36 and 45 years old, with a median of 1,8 and a minimum value of -6,2 (see Appendix 12.4.2, Table 22).

The last two experiences present negative median values for all age groups, meaning they are the least preferred experiences for these segments. Nevertheless, it is also interesting to understand which age groups perceived them as better, although still in a negative sense than others. *"Personalised online shopping through avatar"* (3) seems to be better perceived by the age group between 26 to 35 years old. However, it is the least preferred option for this group when compared with the rest of the experiences (-3,0), and its maximum is still a negative value (-1,8). The age group between 36 to 45 years old presents the lowest median of all segments and experiences in experience 3 (-12,3). Nevertheless, the lowest minimum value can still be found in the age group with 46 or more years old (-23,8) (see Appendix 12.4.2, Table 22).

Finally, *"Personalised online shopping through VTO"* (4) is the second least preferred option for all segments. However, the segment in between 17 to 25 years old is the one segment that is bringing the median value for the whole sample down (-3,8), with a minimum value of -5,3, showing a very low preference, which would not be expected given the fact that younger generations tend to be more tech-savvy. Nevertheless, the age group between 26 to 35 years old is the one that seems to be keener to engage in this experience. However, they still perceive it as one of the least preferred when compared to all the others, presenting a median value of -0,2, and a maximum value of 3,0 (see Appendix 12.4.2, Table 22).

Ranked list of concepts/Product Preference

For respondents aged between 17-25 amongst 90 observations, upper garments ranked first with a median value of 11,5, where the customer would have to accept the mandatory cookies and share personal measurements to get a more personalised with shared measurements online shopping experience. Second ranked is the footwear category, where the customer would be required to only accept the mandatory cookies to have a regular shopping experience. This has a median of 11. Third ranked-once again upper garments with a median of 8,1. Similarly to the above experience refers to regular online shopping (See Appendix 12.4.2, Table 23).

The group segment of 26–35-year old's (N=21), ranked the upper garment category first but also showed an inclination towards footwear. With a median value of 8,5, upper garments were most preferred. The customer would have to accept the mandatory cookies and share personal measurements to get a more personalised experience with shared measurements. For the same personalised online shopping, footwear ranked second with a median of 6,9. Third-ranked once again footwear, but this time with a median of 4,5 for regular online shopping.

The group of 36–45-year-olds amongst 6 observations, was the only segment that ranked the eyewear amongst their top three products. That is, footwear was in first place with a median value of 19, where participants would have to only accept the mandatory cookies in order to have a regular shopping experience. Eyewear was ranked second with a median of 15,2 and would entail the same data privacy sharing settings as above for the same outcome of a regular online shopping experience. Lastly, once again, for a regular online shopping experience with the only requirement of accepting mandatory cookies, upper garments ranked third with a median value of 14,5.

The last age group segment examined were individuals over the age of 45 (N=9). This group portrayed almost identical behavioural preferences to the segment of 26–35 years old. That being said, upper garments ranked first with a median value of 14, and footwear ranked second and third with 9,8 and 9,6 medians, respectively. Regarding the footwear product type preference, first ranked the more personalised online shopping experience with shared personal measurements where the customer would have to accept the mandatory cookies and disclose personal measurements, while third-ranked just a regular online shopping experience with the acceptance of mandatory cookies only.

Relevance Important by Level

Regarding the optimal online shopping experience for each product type per segment, the analysis of choice preference (see Appendix 12.4.2, Table 24) shows that the tendencies are the same for each age group, meaning the results are the same as the previous section. However, the respondents between 26 to 35 years old (N=22) show a slight difference regarding online shopping, with the lowest preference for eyewear. Every segment considers *"Personalised online shopping* *based on shared measurements"* (2) as their least preferred option, except for this prementioned segment, which seems to have less preference for *"Regular online shopping"* (1) (see Table 13). Nevertheless, the difference between both experiences is minimal, *"Regular online shopping"* (1) is rated as -62,7%, while *"Personalised online shopping based on shared measurements"* (2) is rated as -62,3%. he slight difference in age groups might be explained by the fact that age group 1 (17-25) accounts for 71,4% of the sample (93 respondents), while all the other segments account for less than 30 respondents.

Table 6:Optimal Experience for each level per segment

Age segment	Level	Experience	
		Highest Preference	Lower Preference
17-25	**Upper Garments**	4	1
	Footwear	1	3
	Eyewear	3	2
26-35	**Upper Garments**	4	1
	Footwear	1	3
	Eyewear	3	1
36-45	**Upper Garments**	4	1
	Footwear	1	3
	Eyewear	3	2
46+	**Upper Garments**	4	1
	Footwear	1	3
	Eyewear	3	2

<u>*Goodness of fit*</u>

The statistical test known as *"goodness of it"* evaluates how well sample data fits a distribution from a population having a normal distribution. Accordingly, the goodness of fit aims to assess how well the survey report describes the participants' responses. The goodness of fit results from our report indicated that 51.3% of survey participants found satisfaction in the options available, which translated into *"medium fit"*. According to Conjoint.ly, a strong goodness of fit with a pseudo-R2 value over 65% reveals that respondents have distinct feature preferences. A score of under 45% shows that the respondents' selections are more arbitrary due to poor goodness of fit. Hence, our results indicate that respondents do not have very clear preferences for features provided in the survey, but their preferences are not completely arbitrary either. Furthermore, 4.5% of participants' answers consisted of *"None of the above"* answers, meaning these participants were not satisfied with the options available in the survey.

In conclusion, this analysis shows that when exposed to specific data disclosure needs, the respondents tend to prefer the online shopping experience that requires fewer steps, and is less personalised, which translates into *"Regular online shopping"* (1). This shows that personalisation is less valued, considering that the trade-off between willingness to share personal data and perceived added value to the online shopping experience does not exist for most respondents. Nevertheless, upper garments is the top market segment for all the presented personalised online shopping experiences *"Personalised online shopping through shared measurements"* (2), *"Personalised online shopping through avatar"* (3), and *"Personalised online shopping through VTO"* (4). In contrast, eyewear is the least preferred, followed by footwear.

8. Consumer segmentation: Cluster analysis

The initially stated research question examines how customers respond to a VTO feature and how they respond to it given three different types of products: upper garments, eyewear, and footwear. It also explores the trade-off between willingness to share data and the overall added value a VTO adds to the online shopping experience related to different types of products. To assess different customers' perceptions and preferences towards VTOs and evaluate potential users, a cluster analysis was conducted. It adds to the research question by examining the different customer segment's propensity to interact with a VTO regarding their privacy concerns and considering the overall perceived usefulness of the feature. This analysis allowed for creating customer profiles, taking into account the age demographic, which tends to be crucial when exploring technological advances. The cluster analysis was based on the Preliminary Survey's data, Chapter 5 (see Appendix 12.3.2, Figures 13 to 38).

8.1. Methodology

To generate the basis for the subsequent research on Perceptual Maps (Chapter 6) and Conjoint Analysis (Chapter 7), a Preliminary Survey (Chapter 5) was distributed to obtain general insights on customers' perceptions and propensity to interact with VTOs. This survey's data, which collected 228 respondents, was used to conduct the following cluster analysis.

Our thesis research question is focused on exploring the trade-off between willingness to share data and the perceived added value to the shopping experience, measured by the conjoint analysis. In this sense, the cluster analysis aims to examine consumers' perceptions of the relationship between these two factors and generate personas for this market.

The analysis associated *"willingness to share data"* with (i) distrust in how the consumer's data is processed and information on how (ii) comfortable customers feel to virtually try on the different products the group selected according to literature review and insights from expert interviews. The choice of product segments was: (i) upper garments, (ii) eyewear, and (iii) footwear, following literature review and insights from expert interviews. The other component analysed, *"perceived added value to the online shopping experience", was* associated with (i) the perceived usefulness of the VTO feature. Hence, the cluster analysis extracted data from the preliminary survey's questions on (i) gender, (ii) age, (iii) frequency of online shopping, (iv) frequency of VTO usage, (v) privacy concerns related to VTO usage, (vi) perceived usefulness of VTOs and (vii) degree of comfort in virtually trying on different products (upper garments, footwear, and eyewear). These insights were retrieved from questions 1., 6., 10., 15., 17., 19., 21., 22. and 24. of the survey, which can be found in Appendix 12.3.1, Table 12.

A sample of 228 respondents was analysed. The software used for this analysis was IBM SPSS Statistics, given the possibility of converting the data into a numerical scale that would allow for cluster creation. The information on the usefulness of VTOs for the online shopping experience and the level of distrust in how the consumer's data is processed while using a VTO was collected as a rating in the preliminary survey. Hence, by importing the data from the excel file provided by the survey to IBM SPSS Statistics, it was expressed as a scale measurement for questions 6. and 10. The rest of the variables analysed were originally expressed in nominal values. The codes for each conversion can be found in Appendix 12.6.1, Table 26. Although the rating questions 6. and 10. did not need to be converted to characterise the clusters, there was a need to relate them to a nominal value, meaning they would follow the same pattern as questions 15.,17., and 19. did, the only thing changing would be the wording related to them, either *"Useful"* or *"Concern"*. In order to analyse and compare all the data, the variables needed to be unified. The nominal values were converted to ordinal by standardisation and usage of a numerical scale.

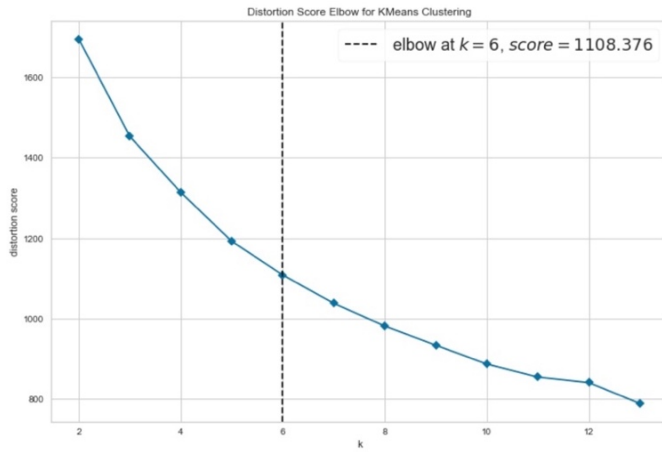
The indicated software was used for the analysis of the variables and the creation of clusters. For the creation of clusters, the group focused on the K-Means cluster analysis, as in this way, we would be able to group the data by maximising data similarity within clusters and minimising data similarity across different clusters (Nainggolan et al. 2019). To identify the optimal number of clusters, we used the Elbow Method to improve efficient and effective K-means performance as Nainggolan et al. (2019) did in their study since the elbow will look for the optimal number of clusters on the K-means method (Syakur et al. 2018). To proceed with the Elbow method and creation of the Scree Plot that would show this optimal number, the group used Python, as this would allow for the elbow to be derived automatically, while in IBM SPSS, the level of objectivity would be lower.

8.2. Results

To obtain the clusters, the data was analysed with the usage of the K-Means cluster analysis. First and foremost, an ANOVA was performed to check the significance of each variable. After running the ANOVA for the first time, we noticed that the p-value for the variables (i) gender and (iv) frequency of VTO usage exceeded the common level of significance, turning these into insignificant variables for the analysis. This means that gender differences have a negligible effect on customers' perceptions of VTOs, and the same happens with the frequency of VTO usage. The latter can be explained by the fact that the majority of the sample (73,7%) has never used a VTO before, which can be seen in Appendix 12.3.2, Figure 18. The variables were then excluded from the analysis, and the group ran a new ANOVA. The new ANOVA table revealed p-values lower than any common level of significance (see Appendix 12.6.2, Figure 68). Hence, we concluded that all of the remaining variables are significant for the study.

This enabled an insight into which variables are suitable to use for clustering. To create clusters, an optimal number of clusters needed to be determined. This has been performed in Python, using the code for the scree plot: elbow method (see Appendix 12.6.1, Figure 65). The elbow method is based on plotting the explained variation as a function of the number of clusters (k). The optimal number of clusters is assessed by determining the point on the line, after which the distortion starts decreasing with a less steep slope and in a more linear way. This point marks the start of the so-called "elbow" of the line (Syakur et al. 2018). With the help of the vertical line, this elbow is found at k=6, meaning the optimal number of clusters for the data under consideration is 6, which can be seen in Figure 9, presented below.

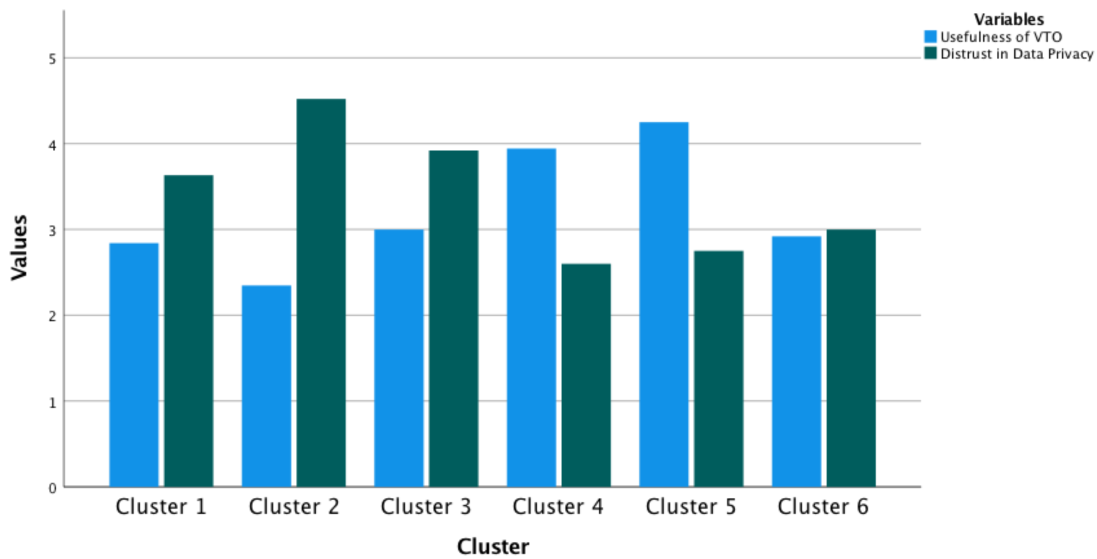
Figure 9: Scree plot: Elbow Method – Python Output



In order to group similar patterns within the observations, the K-Means Cluster Analysis was conducted, taking into consideration the optimal 6 clusters and previously mentioned variables, excluding (i) gender and (iv) frequency of VTO usage. Taking this into account, the initial survey's sample (N=228) has been divided into 6 clusters that are distinctive from each other. With this, a sufficient degree of variety between the clusters indicates the accuracy of the number of clusters chosen. From the sample, cluster 1 (C1) encompasses 19 respondents, cluster 2 (C2) 23, cluster 3 (C3) 63, cluster 4 (C4) 70, cluster 5 (C5) 28, and cluster 6 (C6) 25 respondents of the whole sample (Appendix 12.6.2, Figure 66).

Before moving into the detailed description of each cluster, it is crucial to analyse the general insights one can take from comparing the 6 clusters altogether. The division into clusters enabled a more in-depth understanding of the relationship between willingness to share data and the overall added value a VTO adds to the purchasing experience, related to different behavioural characteristics relevant for each cluster. Based on Figure 10, we can see that the relationship between data privacy concerns and the perceived usefulness of the VTO is negative. When privacy concerns are high, there is a tendency for lower perceived usefulness of the VTO. On the other hand, when privacy concerns are lower, the perceived usefulness of the VTO is higher. This relationship is less noticeable in Cluster 6, but the conclusion is still valid when considering the other five clusters.

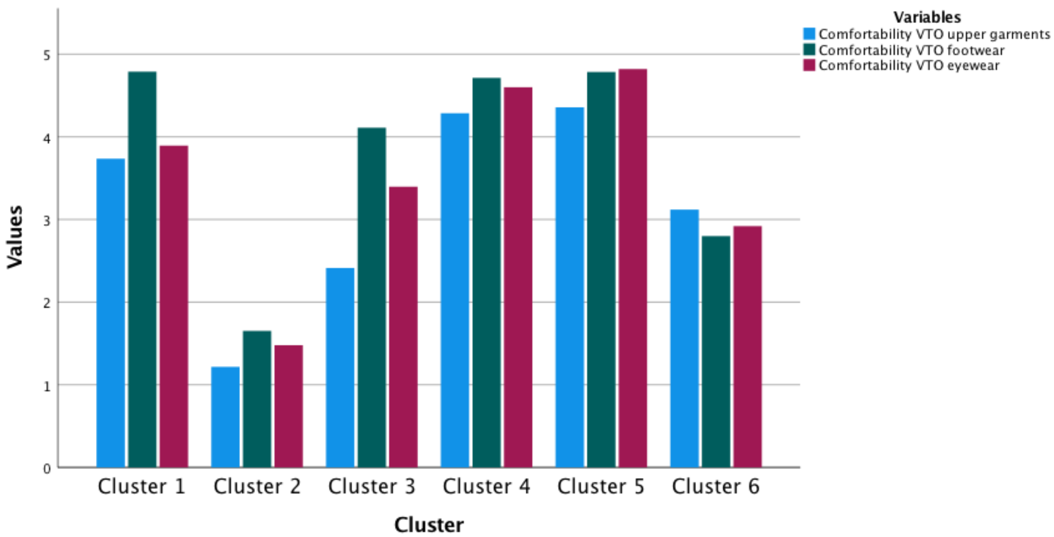
Figure 10: Final Cluster Centres column chart: Usefulness of VTO and Distrust in Data Privacy



When analysing the general pattern for all clusters, it is possible to conclude that the comfort levels in virtually trying on footwear are the highest, except for Cluster 5 and Cluster 6. This can be related to lower levels of body exposure or lower levels of body recognition compared to eyewear or upper garments. Nevertheless, Cluster 4 and Cluster 5 have similar levels of comfort to virtually try on both footwear and eyewear. There is also a general pattern showing that upper garments are the product with less comfortability for the analysed 228 potential consumers, which contrasts with the conjoint analysis the group previously presented. However, Cluster 6 represents an exception since upper garments seem to be the product for which this cluster would be more comfortable to try on virtually.

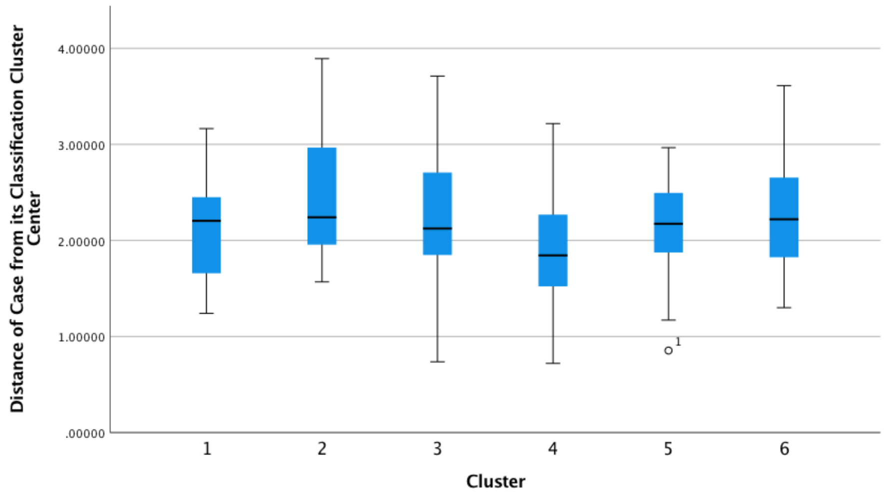
The overall analysis of this chart shows that the products with more potential for this new technology are both footwear and eyewear. However, it is essential to consider the perceived added value to each online shopping experience to guarantee the consumer's engagement with this feature for both product segments. Cluster 2 (N=23) is the one with less availability to engage with this technology, while Cluster 5 (N=28) is the one that represents the highest availability (See Figure 11 down below).

Figure 11: Final Cluster Centres column chart: Comfortability of VTO related to upper garments, footwear, and eyewear



It is now crucial to analyse these distinctions in greater detail, considering the different characteristics of the clusters in order to find possible justifications for their answers. To do so, we focused on the effect of each behavioural characteristic on the overall perception of VTOs and aimed to understand the correlations between each variable.

Figure 12: Simple Boxplot of Distance of Case from its Classification Cluster Centre by Cluster



The boxplot presented above, Figure 12, identifies the outliers within each cluster. In the case of Cluster 5, it is possible to find one standard outlier, represented by a circle in the boxplot, while none of the other clusters presents outliers. This means there is low variability within each cluster, leading to higher statistical significance, assuring that the division of the sample into 6 clusters is related to different patterns across clusters but the same patterns within the same clusters. Although the medians in the clusters seem to be similar, except for Cluster 4, it is noticeable that clusters 2 and 6 have a higher maximum value, knowing that the top whiskers of both clusters are higher than the rest. A difference from these clusters can also be perceived in Cluster 3, knowing that the bottom whisker is lower than the rest, representing the minimum.

<u>*Identification of Clusters*</u>

Cluster 1 – Tech distant

Cluster 1 (N=19) is composed of both men and women with 46 or more years old who shop online yearly. They are inconclusive about the usefulness of the VTO feature, finding it neither useful nor useless. This might mean that this cluster sees potential advantages of VTOs but need to be made aware of how this technology works to give it a proper classification. Moderately high distrust in data privacy is reflected in inconclusiveness about usefulness, potentially leaning towards the perception of VTOs being somewhat useless, reflecting a negative relationship between willingness to share data and the perceived added value. However, this cluster is very comfortable with virtually trying on footwear and somewhat comfortable with virtually trying on eyewear and upper garments (see Appendix 12.6.2, Figure 70).

Cluster 2 – Sceptics

Cluster 2 (N=23) comprises men and women between 36 and 45 years old who shop online less frequently, namely only for specific occasions. They perceive VTOs as somewhat useless, representing the cluster that perceives VTOs as less useful while also being the cluster with the highest distrust in data privacy. High distrust in data privacy is correlated with low perceived usefulness in VTO, indicating a negative relationship between willingness to share data and perceived added value. Therefore, this cluster is very uncomfortable with virtually trying on upper garments and eyewear while somewhat uncomfortable to virtually trying on footwear (see Appendix 12.6.2, Figure 71).

Cluster 3 – Dubious Gen Z

Cluster 3 (N=63) is composed of both men and women between 17 to 25 years old, who shop online seasonally. This cluster perceives VTOs as neither useful nor useless and moderately highly distrusts data privacy. There is a correlation between distrust in data privacy and perceived usefulness, which also reflects the negative relationship between willingness to share data and perceived added value. Higher distrust in data privacy is resulting in the cluster being inconclusive about the usefulness of the VTO. Nevertheless, the cluster is somewhat comfortable with virtually trying on footwear, neither comfortable nor uncomfortable with eyewear, and somewhat uncomfortable with virtually trying on upper garments (see Appendix 12.6.2, Figure 72).

Cluster 4 – Liberal Gen Z

Cluster 4 (N=70) is composed by both men and women between 17 and 25 years old, who shop online seasonally. Although they belong to the same age group as Cluster 3, their behaviour is different. Compared with cluster 3, this cluster perceives VTOs as more useful, rating the VTOs as somewhat useful. This cluster's distrust in data privacy is the lowest of all clusters. However, their distrust in data privacy is still evaluated as medium. The relationship between willingness to share data and perceived added value in this cluster is also noticeable, knowing that, in this case, lower levels of distrust in data privacy correlate to higher levels of perceived usefulness of VTO. The cluster representatives feel very comfortable with virtually trying on footwear and eyewear and somewhat comfortable with virtually trying on upper garments (see Appendix 12.6.2, Figure 73).

Cluster 5 – Liberal Gen Y

Cluster 5 (N=28) is composed by both men and women between 26 and 35 years old, who shop online weekly. Hence, this cluster has the highest online shopping frequency among all the clusters. Moreover, this cluster perceives the highest overall usefulness of VTOs, finding it somewhat useful. Its distrust in data privacy is evaluated as medium, leaning towards somewhat low, also reflecting the prementioned relationship. Somewhat low distrust in data privacy reflects higher levels of perceived usefulness. The cluster representatives feel very comfortable with virtually trying on footwear and eyewear, yet somewhat comfortable with virtually trying on upper garments (see Appendix 12.6.2, Figure 74).

Cluster 6 – Dubious Gen Y

Cluster 6 (N=25) is composed by both men and women between 26 and 35 years old, who shop online monthly. Although they belong to the same age group as Cluster 5, their behaviour can be differentiated. The cluster is inconclusive about the perception of usefulness, finding VTOs neither useful nor useless. Its distrust in data privacy is evaluated to be medium. There is no clear indication of the relationship between willingness to share data and added value since the levels of distrust in data privacy and the perceived usefulness of VTO are both medium. This segment shows low interest in the observed technology and is neither comfortable nor uncomfortable to virtually try on footwear, eyewear, and upper garments (see Appendix 12.6.2, Figure 75).

In conclusion, it would be expected that a higher frequency of online shopping would lead to higher perceived usefulness of a VTO feature. However, the results could be more precise on this matter. Nevertheless, Cluster 5, which has the highest frequency of online shopping (weekly), also shows the highest perceived usefulness of the feature (somewhat useful), and Cluster 2, with the lowest frequency of online shopping (occasionally), also shows the lowest perceived usefulness (somewhat useless). The age group that is more suitable for this market is between 26 and 35 years old, belonging to Cluster 5, Liberal Gen Y since they have lower distrust in data, the highest comfort in virtually trying on all products, and perceive the highest usefulness in the VTO feature.

9. Conjoint Analysis: Recommendations for VTOs for eyewear

This chapter examines the eyewear segment to provide clear recommendations of the ideal VTO experience for brands, as this product had the best customer response in both the preliminary survey (Chapter 5) and perceptual maps (Chapter 6). The literature review revealed the great potential of this segment and the insights gathered from experts (Chapter 4) reinforced the decision to analyse eyewear in more detail. The fact that it was the least preferred product type in the first conjoint analysis may be attributed to the fact that fewer people tend to shop online for eyewear (55 clicks) in comparison to upper garments (181 clicks) and footwear (122 clicks), as derived from the preliminary survey. (See Appendix 12.2.2, Figure 17).

This chapter starts with the methodology, explaining the rationale behind the choice of attributes and levels and the choice of the placement. Finally, it presents the results of this smaller study based on a sample of 100 respondents.

9.1. Methodology

Based on the literature review, expert interviews, and prior results from this thesis, the analysed attributes and levels were chosen in a similar manner to Chapter 7.

Attributes and Levels

This survey aimed to study the importance of the different VTO features and how customers perceive them. By creating different combinations of possibilities, we can identify the most desirable type of personalised online shopping experience through VTO for eyewear. As already mentioned, the choice of attributes and correspondent levels is related to the literature review, expert insights, and results from the previous surveys that were analysed. Differently from the previous conjoint analysis, this one does not encompass endogenous variables, allowing for a greater understanding of the relative importance of attributes in the respondent's choice. This analysis was made to be simpler than the previous one, assuring respondent friendliness. The three attributes and corresponding levels may be found in Appendix 12.6.1, Table 26.

The first attribute, *"Type of VTO,"* was included due to the necessity of providing the different possibilities of personalisation through VTO in order to guarantee user's awareness. Literature review led us to create two levels for this attribute: (i) *"Personalised avatar based on measurements and picture,"* and (ii) *"VTO recording of yourself"*. The second attribute, *"Where to use VTO,"* was included due to the need to evaluate customers' preference of VTO platform, acknowledging that social media filters are essential when analysing AR in the online fashion retail industry. In this sense, the group included three levels: (i) *"Mobile Application,"* (ii) *"Brand's*

Website," and (iii) *"Social media filter (Snapchat/Instagram)"*. Taking into account the findings from the literature review and expert interviews, the last attribute of the user experience questionnaire was "Purpose of Experience", which had two levels - (i) "Fun and Interactivity" and (ii) "Picking the right product (size/fit)". This was due to the need to focus on the user experience for success and the current technology trends of brands striving to provide a fun experience rather than recommending the perfect size. In the conjoint analysis survey, the order of attributes was the same as presented above: (i) *"Type of VTO,"* (ii) *"Where to use VTO,"* and (iii) *"Purpose of Experience"*. This order was considered in order to explore the customer's journey and highlight the ideal features of the VTO.

Initial Survey Setup: Conjoint.ly

The reasons that led the group to choose the software Conjoint.ly were the same as the ones explained in Chapter 7, although in this analysis, we chose to use generic specific conjoint, acknowledging that no restrictions to combinations were needed and the inexistence of brands.

The survey layout was designed with four sections: (i) introduction, where the group presented the different types of VTO and the data privacy associated with each one of them, (ii) two questions that aimed to confirm the respondent was aware of the needed disclosure of data for each experience, (iii) randomly generated choices with no restrictions on combinations, and (iv) additional questions on demographics, such as age, gender, self-esteem, and frequency of online shopping (See Appendix 12.6.1, Figure 76). The survey was designed in the same template as the previous one, allowing the respondents to select a "*None of the above"* option. The number of VTOs for eyewear presented at the same time was set to three, and the number of choices each respondent had to make was 12. "*Type of VTO"* and "*Where to use"* levels were associated with images to increase respondents' friendliness. An overview of the survey layout can be found in Appendix 12.6.1, Figure 77.

Pre-Test and Data Collection

The survey was open from the 19th of November to the 23rd of November 2022. The distribution channels used were the same as those already mentioned in the previous chapters, including social media accounts (Instagram, Facebook, LinkedIn), family and friends' social media groups (Messenger, WhatsApp, Email), and different research groups on Facebook and websites such as Survey Circle.

9.2. Results

Sample characteristics

This conjoint analysis was based on 100 responses, following the sample size advised by the utilised platform, Conjointly. Two demographics were part of the survey: (i) age and (ii) gender. The sample is divided in 58,6% women, 41,4% men, and 0% preferred not to specify their gender. The majority of the sample (59,6%) belongs to the age group between 17 and 25 years old, followed by 28,3% of respondents between 26 and 35, 6,1% between 36 to 45, and 6,1% were 46 years old or more (See Appendix 12.6.2, Figures 78 and 79).

Conjoint Analysis Results

The analysis focused on the preferred VTO experience for eyewear, as well as the relevance per attribute and levels. The data was based on all responses of the sample, which were considered as valuable to include in the analysis.

Attribute importance

The first part of the analysis was the evaluation of the attribute importance. Moreover, it focuses on how important each attribute is relatively to the other attributes across customers, considering that each consumer values different product attributes. As mentioned in the methodology there are three main attributes; (i) *"Type of VTO,"* (ii) *"Where to use VTO,"* and (iii)

"Purpose of experience." The attribute (ii) *"Where to use VTO"* was the attribute with the most importance (50,1%). Next is the attribute (iii) *"Purpose of experience"* which shows an importance of (25,9%). Last there was the attribute (i) *"Type of VTO"* which shows an importance of 24,0%. All the values sum up to 100%. These results showed that the survey respondents have a strong opinion about where to use the VTO and brands should keep this in mind when offering a VTO experience for eyewear (See Appendix 12.6.2, Figure 83).

<u>*Average preference for levels per attribute*</u>

Table 14 displays the average customers' preferences for each level of an attribute compared to the other levels. The values in the table are centred around 0, with positive values indicating a higher preference and negative values indicating a lower preference.

Table 7: Preferences for levels relative to other levels

Attribute	Levels	Preference
Type of VTO	**Avatar based on measurements and picture**	(9,0%)
	VTO recording of yourself	9,0%
Where to use VTO	**Mobile Application**	15,9%
	Brand's Website	19,3%
	Social Media Filters (Snapchat/Instagram)	(35,2%)
Purpose of Experience	**Fun and interactivity**	(13,8%)
	Picking the right product (size/fit)	13,8%

The first attribute shows that the preferred level was (i)*"VTO recording of yourself"* with 9% rather than an (ii) *"Avatar based on your measurements and picture"*. We interpreted this as medium high level of preference. The second attribute was *"Where to use VTO"* and consists of three levels: (i) *"Mobile application,"* (ii) *"Brand's website"* or (iii) "*"Social media filter (Snapchat/Instagram)*." The preference of the respondents was to have the VTO experience for eyewear on a "*Brand's website*." This level scored 19,3% which is a high score of preference. Secondly, the respondents prefer that the experience is hosted on a *"Mobile app",* with 15,9%.

Social media is not a popular platform with a very high negative score (-35,2%), which showed a high dispreference.

The final attribute, *"Purpose of experience,"* showed that potential customers have the preference of a brand's focus on the level (i) *"picking the right product"* rather than (ii) *"fun and interactivity."* In e-commerce, customers potentially care to reduce the perceived risks of shopping online. They cannot physically examine the products. (Do et al., 2019). Therefore, when shopping online they aim for the right product. Another explanation might be the frequency of the product purchased. Eyewear is not a product that is bought frequently. This makes the tendency of buying the right product higher.

Distribution of preference for levels per attribute

The chart presents the distribution of preferences for various levels within each attribute across customers considering that each consumer likes (slightly or greatly) different levels (See Appendix 12.6.2, Figure 84). The graph shows the percentage for which respondents picked a level compared to the other attribute levels. Within the attribute *"Type of VTO"*, 63,5% of the respondents preferred the *"VTO recording yourself"*. The second attribute, *"Where to use the VTO,"* 46,9% preferred the *"Brand's website"* followed by the use of a *"Mobile Application"* with 39,2%. Together they formed a significant majority. When interpreting these results, we concluded that our respondents are not looking for Fun and interactivity, so the last level *"Social Media"* is not preferred by them. The last attribute was the "*Purpose of experience*," and, as previously mentioned, the majority (67,5%) preferred *"Picking the right product (size/fit)"* over *"Fun and Interactivity"*.

Ranked list of some product concepts as preferred by customers

To understand the consumer preferences towards a VTO for eyewear, Conjoint.ly ranked a list of value per attribute. More specifically, the options shown in Appendix 12.6.2, Table 27 serve as a list of every potential combination that was shown to respondents and sorted in accordance with their top choice profiles. There are 12 rankings in total that indicate the added value to the customer's experience.

We can conclude that the highest value was added by the combination of levels; *"VTO recording yourself,"* on a *"Brand's website"* with the purpose of *"Picking the right product (size/fit)"* with 20,1. In the case of eyewear, it was interesting how hedonic values were perceived as less important when comparing to other products. The second experience customers valued highly was the combination mentioned above but instead of using the *"Brand's website"* the option of the *"Mobile application"* was used and valued at 18,5. Combinations with the third level of *"Where to use the VTO"*, which was the *"Social Media filters (Snapchat/Instagram)"*, it was only mentioned on the 9th place with a negative value to customers of -5,9.

Next, we change the *"Type of VTO"* to *"Personalised avatar based on measurements and picture."* The levels with the most value in this case are *"Brand's website" and the purpose of "picking the right product (size/fit)."* This combination is still valued relatively high with 11,5. When the type of VTO changes to *"Mobile application"* the value of the experience drops to 9,9. Lastly, we will discuss what combinations brands should not focus on. This includes the combinations *"VTO recording of yourself"* when used on *"Social media filters (Snapchat/Instagram)"* with the purpose of *"Fun and Interactivity."* Respondents valued this combination with a negative -19,1. The worse combination possible is with the type of VTO *"Personalised avatar based on measurements and picture"* when hosted on *"Social media"* with the purpose of *"Fun and interactivity"*. Customers did not value this combination.

Goodness of fit

Goodness of fit results derived from our report indicated that 57.7% of survey participants found satisfaction in the options available, which translated into "medium fit." Only 8.7% were not satisfied with options available in the survey, choosing the *"None of the above"* option.

Additional questions

In order to validate whether the usage of a VTO feature outweighs the costs of data disclosure, we asked participants about their preferences. The options available were *"Avatar based on measurements and picture," "VTO recording of yourself"*, *"Both"*, and *"None."* The majority of the respondents find both the avatar and the VTO self-recording option as beneficial consisting of 38,4%, while 31,3% prefer VTO self-recording, and only 21,2% selected avatar based VTO. Lastly, 9.1% of the respondents selected that they would not select either of the 2 options which outweigh the costs of data disclosure. Furthermore, we examined the frequency of participants' online purchases. The options presented to them ranged from *"Daily"*, *"Weekly"*, *"Monthly"*, *"Seasonally"*, *"Yearly"*, *"Occasionally"*, and *"Never."* The most selected option was *"Monthly"* online purchases at 34,3%, followed by the second highest selected option of *"Weekly"* purchases at 27,3% (See Appendix 12.6.2, Figures 80 and 82).

We also assessed the mediating role of self-esteem in the VTO feature selection process for customers' online shopping experiences. This question was structured using a star rating technique where the users could rank attributes on a 5-star scale. The rating employed stars which indicated consumer preferences ratings of their self-esteem, with 1 star indicating the *"Very low"*, whereas 5 stars the *"Very high"* option. The mean value of the sample is 3,8 and the median value is 4, which means that of the 100 respondents, 51,5% selected their self-esteem ranking at 4 starts indicating *"High"* self-esteem. This was followed by 22,2% of respondents ranking their self-esteem at *"Moderate"* with 3 stars. Moreover, 19,2% of respondents expressed *"Very high"* self-esteem at 5 stars. Lastly, very few of the respondents had *"Low"* self-esteem, 6.1%, and *"Very low"* self-esteem at 1% (See Appendix 12.6.2, Figure 81).

In conclusion, it is evident that customers place a significant importance on the platform of the VTO option available to them. Furthermore, the placement accessibility for eyewear VTOs is an essential determinant for the type of VTO customers intend to select as well as the purpose of using this technology. The selection of VTO self-recording option is often contingent upon whether customers are well aware of the explicit data disclosure required for their other option, namely a personalised avatar VTO. One explanation could be that customers care to lessen the perceived risks associated with online shopping. This supports our hypothesis that when customers are reminded about the privacy disclosure, they tend to perceive a higher privacy risk and, as a result, are less likely to share their personal data. Furthermore, our inquiry about customers' self-esteem allowed us to understand its association with VTO type selection. As we discovered a correlation between high self-esteem in this sample of respondents and the fact that most respondents chose the *"VTO recording of yourself"* as their preferred VTO feature, selection of low self-esteem would result in choosing the *"Personalised avatar based on measurements and picture"* option.

10. Discussion

10.1. Limitations and Further Research Opportunities

The following chapter examines the research limitations and suggests possible directions for future research.

Literature Review: It is well-documented that the implementation of video recording technologies, or VTOs, in the fashion retail industry is a relatively new phenomenon. As such, the available literature on the topic is limited, and most research on advanced technology in online retail does not specifically focus on consumer behaviour and the perceived added value of VTOs from a customer's perspective. This may make it challenging to conduct a comprehensive literature review on the topic. However, conducting interviews with experts in the field or examining related research on advanced technology in online retail can provide valuable insights into the use of VTOs in the fashion industry. Further research on the topic is necessary to gain a deeper understanding of the impact of VTOs on consumer behaviour and the perceived value of these technologies.

Our research examined consumer behaviour and the perceived added value of the VTOs towards three specific types of products: (i) upper garments, (ii) footwear, and (iii) eyewear. However, this resulted in a few complications when preparing the literature review. Although VTOs apply to many different product categories, more research is needed when focusing on the products themselves. We interviewed and connected with experts who specialised in VTOs for the respective product categories to gain more insights and information that was not available through other sources, such as literature. However, we acknowledge that further research into other product categories that offer VTOs is highly recommended to gain more insights about the added value per product.

Expert Interviews: When conducting the expert interviews, we gathered opinions from various stakeholders in the VTO industry. Most of these participants were from technology companies, which yielded valuable insights. We managed to receive input from an expert in the area of eyewear VTOs with direct affiliation to the fashion retail industry but were unable to do so for the product categories of footwear and upper garments. This is a common challenge when attempting to engage with industry experts (Bogner, Littig, and Menz 2019). A way to address this issue is to assign one person in the group to be responsible and entirely dedicated to connecting and networking with fashion industry experts in case a greater time frame is available to develop our thesis.

Sample: One further limitation identified in our research is that the data gathered from our survey is susceptible to sample size bias. While we distributed our surveys through a wide range of networks and social media channels, the sample only represents a small portion of the overall population. As Rahman et al. (2013) explain, sample bias can lead to incorrect conclusions and underperforming prediction models and can also impact a study's external validity. To address this limitation in future research, we recommend establishing more specific research questions and carefully selecting a representative sample from the population of interest. For example, distributing the survey to Portuguese individuals within a specific age range who have used VTOs could reduce bias and increase the generalizability of the study. This can help ensure that the sample is representative of the studied population and can improve the generalizability of the study's findings.

One significant issue arising from the limitation of sample size bias is the impact on the clusters formed from the data obtained from our conjoint analysis. Because participants were divided into smaller groups (clusters), some of these clusters had a sample size of less than 30. A sample size of less than 30 is not considered sufficiently large to accurately forecast population characteristics such as the mean and standard deviation, which reduces the value of the analysis. To address this limitation in future research, we could distribute the survey to specific age groups to ensure that each target group has at least 30 participants, which would improve the validity and reliability of the data.

Additionally, the uneven distribution of respondents by gender in the preliminary survey (61.7% female and 38.3% male) can also pose a limitation and impact the results obtained. To avoid this limitation in future research, we could keep track of respondents who wish to participate in our surveys and target remaining genders once the desired or sufficient number of male respondents has been achieved. This would help ensure a more balanced and representative sample, which would improve the generalizability of the study's findings

Another limitation of our research is the high proportion of participants who had not previously been exposed to VTOs. In the preliminary survey 73.7% of respondents had not tried a VTO feature and relied on their imagination to answer the survey questions, which may not always be accurate or adequate for research purposes. In future research, it would be more beneficial to obtain results from participants who have used VTOs, as it is a relatively new technology that is expected to continue evolving. To achieve this, it would be necessary to focus on more defined groups of participants and create a survey specifically targeting individuals who have experience with VTOs. This could improve the validity and reliability of the study's findings and provide a more comprehensive understanding of the impact of VTOs on consumer behaviour.

Perceptual Maps: Upon conducting the perceptual maps, we encountered two limitations in our research. The survey which provided the data for the perceptual maps measured six factors. One of those factors was *"Data privacy concerns"* and was measured on the same scale and direction as the other factors. Furthermore, the other factors, "Quality of recommendations", "Interactivity", "Usefulness", and "User-friendliness", are all measured in the same positive direction and should be contradictory to the *"Data privacy concerns".* To address this issue, we reversed the factor *"Data privacy concerns"* scale from 1-5 to 2-4.

Secondly, the factor analysis performed to present the perceptual map derived a cumulative variance of 1. This indicates that our model is not suitable for the research we conducted, as it is not possible to achieve a perfect model. Factor analysis is typically used to reduce the number of variables to one or a few factors that explain the variables. In our model, there is only one item for each variable, so reducing the number of variables is not possible. Further statistical research into this topic could lead to a better understanding of the cumulative variance in this model.

Conjoint Analysis: When conducting the conjoint analysis, more limitations were revealed. Firstly, the respondents exhibited a status-quo bias, focusing their attention on what they are accustomed to purchasing online instead of making the most rational choice (Kahneman, Knetsch, and Thaler 1991). When participants were only considering eyewear, they tended to perceive more value in VTOs for this product than the others, as was shown in both the preliminary survey and perceptual maps analysis. This limitation could be addressed by including an introduction in the survey explaining to the participants that they should make unbiased decisions in the survey they are about to take part in, specifically to connect products with VTO technology rather than online shopping.

Another limitation related to the conjoint analysis is the choice of a brand-specific conjoint analysis. This method was employed in our analysis due to its ability to select all the accurate combinations for respondents, considering that the attributes *"Online shopping experience"* and *"Data privacy concerns"* are endogenous variables. Restrictions were implemented within these two attributes to generate only valid outcomes. These restrictions limited the data insights gathered and made the results less constructive. Different outcomes and opinions were gathered when comparing the surveys to the conjoint results. This could be due to the limitation of the survey set-up, or perhaps survey participants did not value eyewear as much as in the other surveys. Therefore, a second conjoint analysis was conducted to address the previous limitations.

10.2. Findings and recommendations

The following section provides a summary of key research findings, as well as recommendations for retailers and brands offering or considering the implementation of a VTO feature. It is organised according to the stages of the research process and the types of analyses performed.

Expert interviews suggested that a VTO feature offers a (i) fun and interactive shopping experience, (ii) reduces the number of product returns and (iii) adequately displays product visual characteristics. However, there is a consensus that more advanced technology is required to improve recommendation quality and personalisation.

How do customers respond to VTOs?

The preliminary survey revealed that most participants have not yet used a VTO, but they demonstrated a willingness to try the technology. This is likely due to the fact that VTOs are still in the early stages of implementation and are only being utilised by a few brands. It has been established that quality of recommendations, personalisation, and interactivity are the primary drivers for customers to use VTO feature. This has been supported by experts' opinions. Moreover, customers have been shown to perceive a higher value in brands that offer VTO services, indicating that it is a beneficial investment for fashion retailers. Our analysis revealed that customers were hesitant to use VTO features due to data privacy concerns. Privacy was perceived as a risk, associated with distrust in how the data is being processed. This finding is in line with research conducted by Ivanov, Mou, and Tawira (2022), who argued that privacy concerns negatively affect the adoption intention towards a VTO. Additionally, Ariffin, Mohan, and Goh (2018) suggested that customers' intentions to make online purchases are adversely affected by perceived risk, particularly security risk.

The underlying motivations for customers to supply personal information to marketers in order to facilitate the understanding of their needs and preferences through data collection remains uncertain (White 2004). Our analysis revealed a lack of clarity regarding the information customers are willing to provide to use a VTO feature. The preliminary survey indicated customers are more likely to share body measurements or their picture than to record themselves. This finding can be applied to the study conducted by Feng and Xie (2018), which correlated privacy concerns to customer's desired viewing condition (e.g., self-viewing or other viewing). Viewing oneself wearing a product is likely to result in higher degrees of perceived intrusiveness and more negative app sentiments among users with significant privacy concerns than viewing others.

Additionally, our analysis demonstrated that the lack of human interaction, and the inadequate quality of recommendations contribute to customers' reluctance to use VTOs. This raises an intriguing point that, while fitting recommendations are a primary motivator for customers to use VTOs, the poor quality of these recommendations can be a deterrent. Conversely, Baytar, Chung, and Shin (2020) argued that VTOs augmented with AR technology yielded accurate sizing and colour information compared to a physical try-on of a dress. Additionally, it was noted that clothing's visual characteristics and compatibility with other items were satisfactorily predicted, resulting in a favourable attitude towards AR and the actual dress, as well as an increased intent to purchase. Therefore, we suggest that further research be conducted on customer's satisfaction with the quality of VTO recommendations. We believe that there is potential for improvement in the development of VTO recommendations, in order to provide more accurate suggestions and a smoother experience.

<u>How do customers perceive VTOs related to different products?</u>

In order to gain insight into how customers perceive the VTO experience regarding different types of products, 5 impacting factors were evaluated. It was concluded that factors such as *"Usefulness"*, *"User-friendliness"*, *"Interactivity"*, and *"Quality of recommendations"* had a positive impact on customers' perception of VTOs and are closely related to the perceived added value to the online shopping experience. Our findings support the research of Pantano, Rese, and Baier (2017), which showed direct influence of perceived usefulness and enjoyment on attitude towards AR, highlighting the hedonic and utilitarian value of the technology utilised in the shopping experience. Furthermore, our findings are in accordance with the research of Plotkina and Saurel (2019), which concluded a direct influence of hedonic (e.g., perceived enjoyment) and utilitarian value (e.g., perceived usefulness, perceived ease of use, perceived convenience) on customer's attitude towards the technology used. Additionally, Yang and Wu (2009) reached a similar conclusion, indicating that vividness and interactivity are determinants of telepresence that have significant impact on hedonic and utilitarian value. Contrarily, the factor *"Data privacy concerns"* negatively influences customers' perceptions to virtually try on different products. This is in accordance with Harborth (2019), who noted that social consequences, privacy, security, and the lack of additional value through the use of AR are key considerations for the adoption of new technologies. Correspondingly, Poushneh (2018) argued that when AR technology violates the desire of personal data privacy or delivers unsatisfactory augmentation quality, customers are less likely to use AR.

Our perceptual map analysis revealed the associations of the specified factors and the product categories under consideration: i) eyewear, (ii) footwear, and (iii) upper garments. It has been concluded that customer perceptions of eyewear are positively associated with a range of factors, including *"Usefulness," "User-friendliness," "Quality of recommendations"* and *"Interactivity."* Eyewear is the highest ranked product category for VTOs amongst all factors due to its positive influence on the respondent's attitudes. This suggests that customers perceive the feature to be of value to their online shopping experience, leading to increased willingness to use the feature. This finding is consistent with the findings of Pantano, Rese, and Baier (2017), which noted a positive customer's attitude for eyewear. Furthermore, our research revealed that customers have significant data privacy concerns regarding virtually trying on upper garments, compared to the other two product categories. Customers had generally neutral to positive attitudes towards the rest of the factors, ranking this product category as second. The reluctance of customers can be attributed to the high degree of body exposure and recognition needed when using this feature for upper garments. Footwear VTOs were perceived as the least useful and interactive in terms of providing customers with a user-friendly shopping experience and quality of recommendations. This product category was found to be the least associated with factors that positively influence customers' online shopping experiences, thus not providing additional value. Additionally, this product category was rated low on data privacy concerns, which can be explained by the fact that customers perceive data sharing of their feet as less intrusive, making them less reluctant to share such information.

<u>Is there a trade-off between willingness to share personal data and the perceived added value to the shopping experience related to different types of products?</u>

A key finding retrieved from the first conjoint analysis is that respondents tend to be more reluctant towards the usage of VTOs (avatar and recording), when they are faced with the realisation of the amount of data, they need to disclose to benefit from a personalised experience related to different products. Hence, the cost of data disclosure outweighs the perceived added value (benefit) of the experience. This is in line with the privacy calculus theory (Culnan and Armstrong 1999), which describes the disclosure intention as the outcome of an evaluation of perceived risks and benefits. Consequently, we posit that customers' data privacy risks outweigh the perceived benefits of the personalised experience. When customers are presented with clear data sharing requirements, they tend to have a lower perception of value from personalisation compared to when asked about VTOs in a more general context. Our findings suggest that high data privacy concerns lead to a decreased willingness to engage with AR technology compared to other online shopping experiences, such as regular online shopping and personalised online shopping utilising shared measurements.

Our results indicated that AR-based experience was not the most preferred, yet it is possible to draw conclusions regarding the optimal product categories for each experience. Upper garments constituted the optimal product type for both personalised avatar try-on and self-recorded VTO. Footwear was the least desirable product category for personalised avatar try-on, whereas eyewear was the least desirable product category for self-recorded VTOs. It is essential to investigate the underlying rationale behind the fact that eyewear was determined to be the highest-ranked segment in the preliminary and perceptual maps surveys yet was deemed to be the least preferred option for most online shopping experiences explored in the conjoint analysis. Recalling Appendix 12.2.2, Figure 17, it is evident that eyewear is the least procured online shopping item, garnering only 55 clicks out of a sample of 228 respondents. Conversely, upper garments are the most popular online shopping item, with 181 clicks.

The finding of our conjoint analysis demonstrates that upper garments are the most popular item across 3 of the 4 presented online shopping experiences, which conflicts with the results of our previous analysis, which identified eyewear as the top product segment in terms of customer preferences. Additionally, eyewear has been correlated with positive attitudes towards AR usage and purchase intentions in the literature. Consequently, we posit that the respondents were affected by the *status-quo* bias, focusing their attention on what they are used to buy online instead of the most reasonable choice (Kahneman, Knetsch, and Thaler 1991). Our preliminary analysis showed that participants usually shop online for upper garments, which could be a factor influencing their choices in the conjoint survey. Additionally, when asked about each product category separately, participants demonstrated a higher value recognition for VTOs with regards to eyewear. Consequently, we believe that this supports the *status-quo* bias. Our research has revealed that two major aspects shape customers' attitudes and preferences towards VTOs. Firstly, customers are less willing to use VTO technology when they are confronted with an explicit data sharing requirement.

Secondly, the *status-quo* bias can be associated with customers' decision making towards online shopping with AR-based technology. Further research is suggested to further explore these findings.

How do preferences and perceptions differ across customer segments?

Our research indicated that the most appropriate demographic for the VTO market are individuals aged 26-35 belonging to Cluster 5. This customer segment is named Liberal Gen Y, since they have lower distrust in data, higher comfort in virtually trying on all products, and generally perceive the highest usefulness in the VTO feature. A distinct characteristic of this specific segment is that they make online purchases on a weekly basis, meaning that technology renders a significant part of their daily life, which could also explain their low distrust in the use of their personal data. The trust in their data privacy is directly related to the perceived usefulness of the VTO, which, for this case, is very high. This customer segment can be described as having hedonic values which are defined as more subjective, and fulfil purchases primarily for pleasure, amusement, and stimulation (Childers et al. 2001), with the potentiality of increased enjoyment of the shopping experience.

A secondary cluster that can be taken into consideration is Cluster 4, namely the Liberal Gen Zs. The segment comprises individuals aged between 17-25 who shop seasonally. A further point of differentiation is that this segment perceives VTO technology as useful and has the lowest distrust in data privacy amongst all clusters. The higher levels of perceived usefulness of VTOs correlate to the lower levels of distrust in data privacy. Similarly, to the Liberal Gen Ys, these customers can also be characterised as having hedonic values, which encompasses potential entertainment and enjoyment of the shopping experience (Babin, Darden, and Griffin 1994).

We believe that it would be considerably more beneficial to target this market group that is likely to be interested in VTO technology amongst different types of products and open to sharing the personal data for a more personalised online shopping experience, rather than a very large audience. According to our research, the specific customer segment that companies should avoid targeting with their VTO technology are the Sceptics, which belong to Cluster 2. These shoppers are between 36 and 45 years old, shop online occasionally, perceive VTOs as somewhat useless, and show the highest distrust in data privacy. This group of customers can be further classified as utilitarian shoppers, who are typically regarded as effective, logical, and task-driven (Childers et al. 2001). Hence, using a VTO would make their shopping experience less effective, as more unnecessary features would be added towards their shopping journey. As we have thoroughly examined the trade-off between data privacy and the perceive usefulness of VTOs, it is only prudent for a company to avoid this certain customer segment.

<u>What are the ideal features for a VTO when trying on eyewear?</u>

As previously mentioned in Chapter 9, the second conjoint analysis performed aimed to assess the ideal VTO experience when trying on eyewear in order to provide recommendation to online fashion retailers. However, we discovered that the platform in which customers can use VTOs also plays an important role in their decision to use the feature for eyewear during their online shopping experience. More specifically, when taking into consideration all the attributes examined; type of VTO, placement of the VTO, and the reason for which participants would use it, the most valuable experience combination was VTO recording yourself, in a brand's website and for picking the right product for eyewear. Again, we acknowledge the difference between participant's disclosure behaviour. Our preliminary survey showed a higher preference for uploading a personal image for a personalised experience compared to recording themselves to use the VTO. However, when respondents were highly aware of the explicit data disclosure needed for the customisation of an avatar, which requires an upload of a personal picture, customers tend to choose the VTO recording option. The reasoning behind this may be due to the fact that the storage of data is perceived to be higher in this specific case, rather than a real-time scanning of the body, which confirms our reasoning that when reminded about the privacy disclosure, customers perceive higher privacy risk and their willingness to share personal data decreases.

We believe that this further represents a meaningful insight to customers' self-esteem. Furthermore, we correlate high self-esteem in this sample of respondents to the fact that the majority of respondents selected their preferred VTO feature as the *"VTO recording of yourself."* On the other hand, if participants had low self-esteem, the selection of the *"Personalised avatar based on measurements and picture"* would have been selected. This explanation derives from a belief that participants with higher self-esteem would feel more comfortable seeing themselves on a screen and hence virtually trying on clothes. This can be correlated with expert's opinion about customer's desire to look their best when engaging with advanced technology shopping experiences. Customers with lower levels of self-esteem could be hesitant to use VTO recordings of self. Hence, they would prefer the personalised avatar option, since they would sense a better version of themselves. Furthermore, this corresponds with the research conducted by Merle, Senecal, and St-Onge (2012), which argued that body esteem and perceived VTO self-congruity play a crucial role in directly or indirectly increasing hedonic and utilitarian value, which increases purchase intention. Body-esteem has been proven to positively influence self-congruity and confidence fit. A lower level of body-esteem has been correlated with viewing a VTO self negatively, consequently resulting in perception of VTO as less congruent. Hence, we conclude that further research should be done on the topic of body-esteem and VTO personalisation option. Moreover, retailers should target specific segments that are open to such technology, considering the body-esteem factor.

Recommendations to online fashion retailers

1) The placement used for a VTO feature greatly impacts whether customers are willing to use the technology in their shopping journey. From our results, the brand's website is the most preferred platform for the use of VTO. This might relate to the fact that customers often prefer to buy directly from the brand if given the option. Furthermore, a brand's website is 57% more likely than a retailer's to be where customers begin their online shopping journey (Zorzini 2015). Therefore, we strongly encourage online retailers that are using or are planning to use VTOs, to do so through their brand website to attract more customers and achieve maximum customer satisfaction.
2) We highly recommend that brands use the *"VTO recording of yourself"* option to personalise a customer's online shopping experience. According to Eyewear VTO experts (Chapter 4), eyewear is not exactly a product for which customers make an impulse buying decision but requires careful consideration. Customers need a visual representation of how the eyewear would look on themselves because it improves overall customer satisfaction which can positively influence the customer's perception of a brand. Providing the option *"VTO recording of yourself"* will achieve exactly this goal.
3) Moreover, according to the upper garments VTO expert (Chapter 4), this category shows great potential for VTO usage in the future, as demand for a more personalised online shopping experience is highly anticipated by customers. However, from our preliminary survey analysis we found that there is great potential to improve the online shopping experience by establishing a more precise VTO technology for upper garments since fitting recommendation and sizing is as not as precise as in eyewear (See Appendix 12.2.2, Figure 36). Offering VTOs for upper garments will be beneficial for fashion

retailers as they could differentiate themselves from competitors by providing a unique experience.

4) Brands should focus on providing sufficient VTO technology that will supply accurate and personalised fitting and styling recommendations. Results from the second conjoint analysis present that for the most optimal experience combination, the reason to use a VTO for eyewear products is to pick the right product. This was also confirmed by an EyewearVTO expert, who suggested that fitting and styling recommendations play an essential role in the customer journey. They help customers in their decision-making process and offer convenience since customers are still trying to determine their style. Therefore, allowing them to use VTOs immensely contributes to finding out what they like the most about themselves.
5) On a last note, individuals who adhere to more liberal ideologies frequently distinguish themselves from other customers by selecting products with distinctive features and are more interested in trying out new products (Ordabayeva 2018). Therefore, we strongly advise retail fashion companies that already use VTOs or are planning to implement this technology for their brands, to target Liberal Gen Ys and potentially Liberal Gen Zs, due to the potential of these two segments.

Conclusions

Based on our findings, customers show an inclination towards a regular online shopping experience when given the option to choose between a highly personalised VTO experience and a regular online shopping experience. When presented with the data sharing requirements of a personalised shopping experience, customers perceive a decreased added value due to heightened awareness of data disclosure. Our conjoint analysis revealed that regular online shopping was the most preferred experience, followed by personalised shopping through shared measurements. This indicates a negative correlation between data disclosure and the perceived added value of the personalised experience when customers are reminded of the data they must disclose. Concurrently, they generally present a positive attitude towards VTOs. The product category that generates the highest ratings in terms of usefulness, quality of recommendations, interactivity and user-friendliness of the experience is eyewear. The product category associated with the greatest data privacy concerns is upper garments, and the one with the lowest is footwear. The product category that customers choose is upper garments. This can be explained by the *status-quo* bias and the way it influences their attitude and preferences towards VTO. When they are presented with all possible product categories, they choose the one they would more frequently buy online. The cluster that is more likely to virtually try on the different product categories examined is the Liberal Gen Y. These individuals are aged between 26-35, make online purchases on a weekly basis, with lower distrust in data, higher comfort in virtually trying on all products, and generally perceive the highest usefulness in the VTO feature. Lastly, customers tend to disclose fewer personal data when exposed to explicit data sharing requirements, opting for less personalised options. However, in the case of avatar, where sharing a personal picture is required, and with awareness of picture being stored, they tend to choose self-recording VTO, although more data sharing steps are required. Hence, the optimal VTO experience for eyewear comprised of using a self-recording VTO option, on the brand's website, with the objective of picking the right product.

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Appendix

12.2.2 Results

Figure 13: What is your gender?

Figure 14: How old are you?

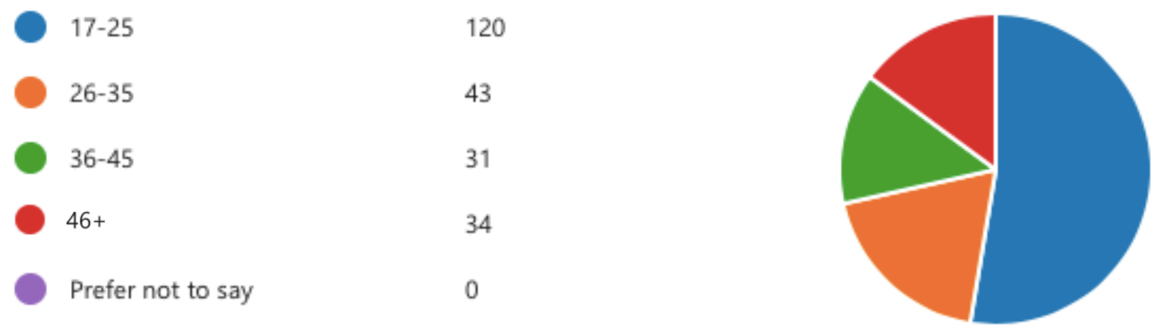


Figure 15: What is the total annual income of your household (before tax and deductions, but including any benefits/allowance)?

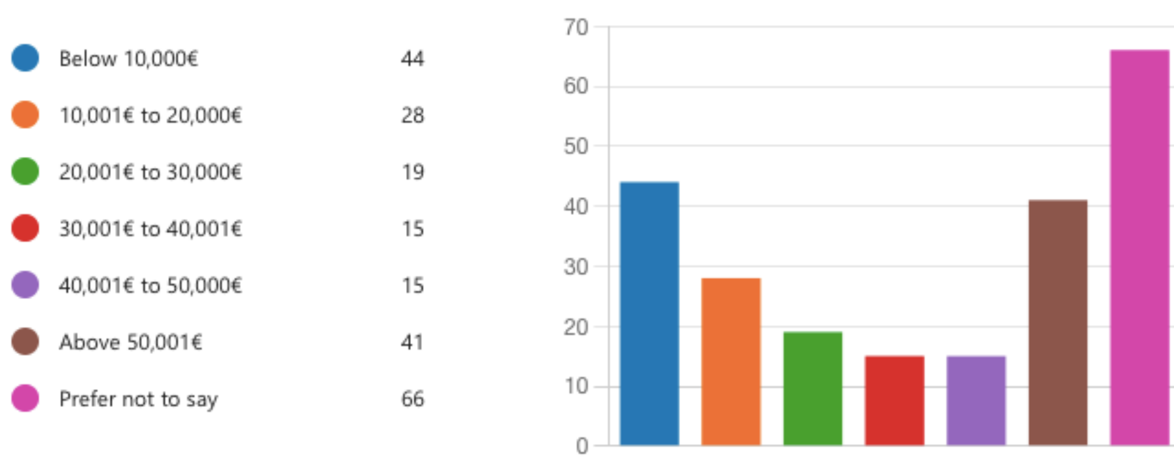


Figure 16: How often do you shop online?

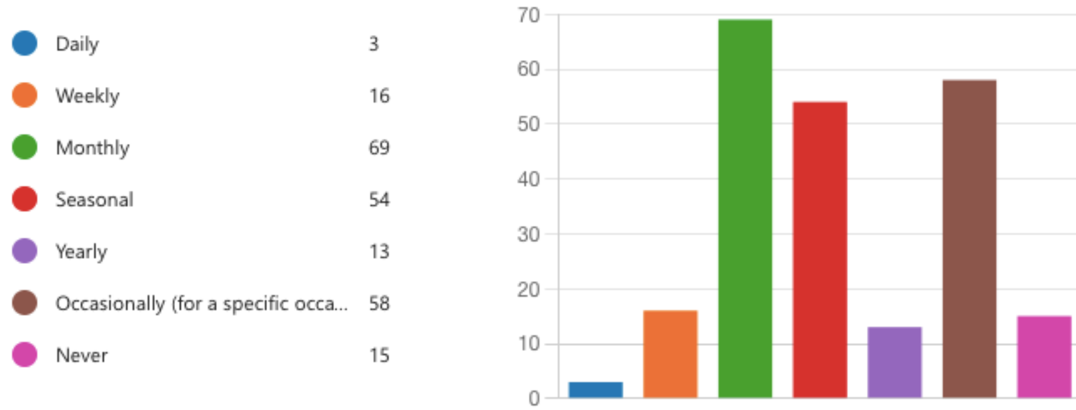


Figure 17: What type of fashion products do you buy online? (choose 1 or more options)

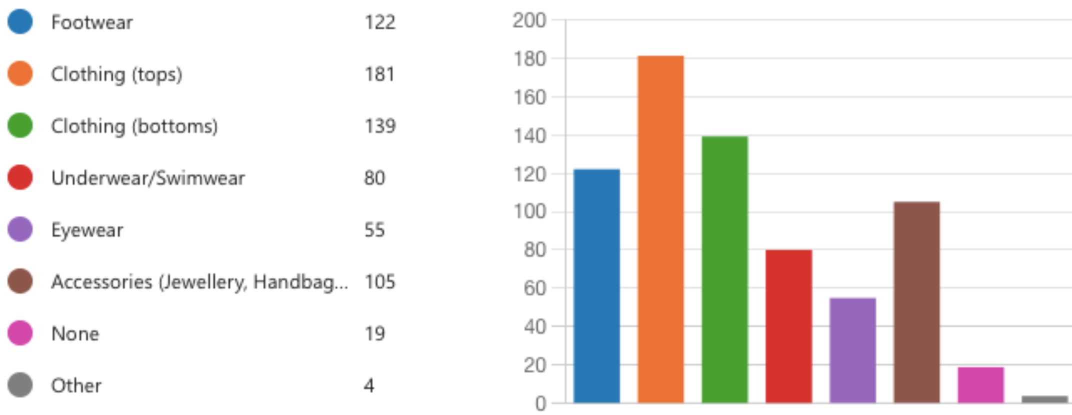


Figure 18: How often do you use a virtual try-on feature when shopping online for fashion products?

Figure 19: Would you consider using a virtual try-on feature to improve your online shopping experience again or in the future?

Figure 20: What are the main reasons for using a virtual try-on when shopping online? (choose 1 or more options)

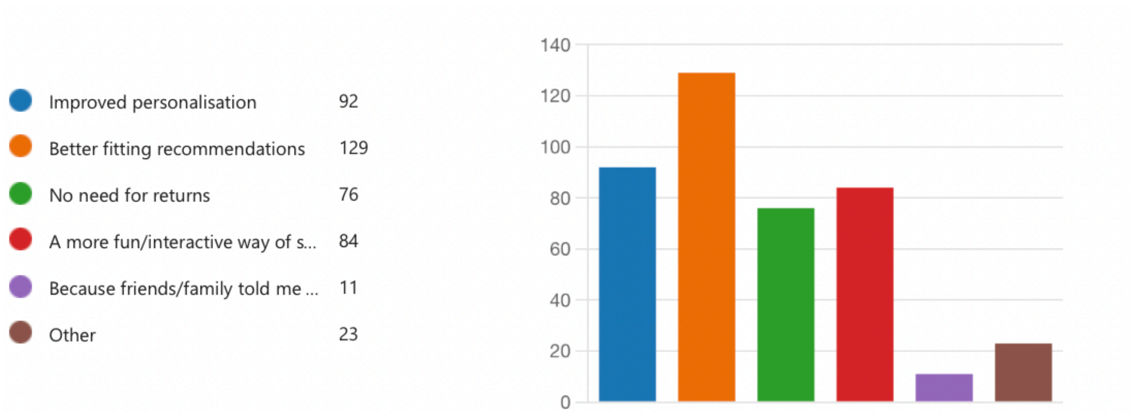


Figure 21: How likely would you upload measurements/photo/recording on a platform to use a VT0?

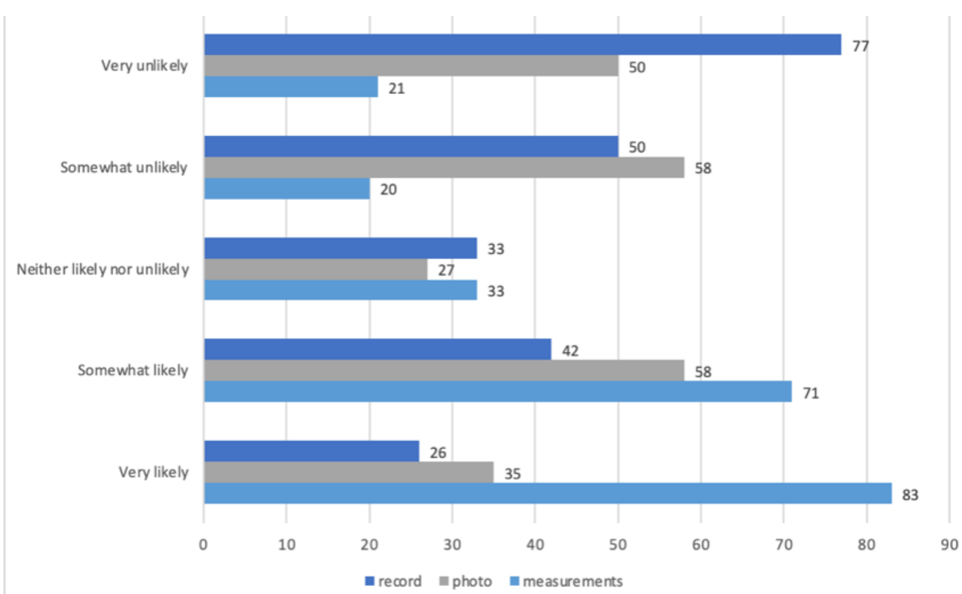


Figure 22: Do you see additional value in brands or fashion retailers that offer virtual try-on feature?

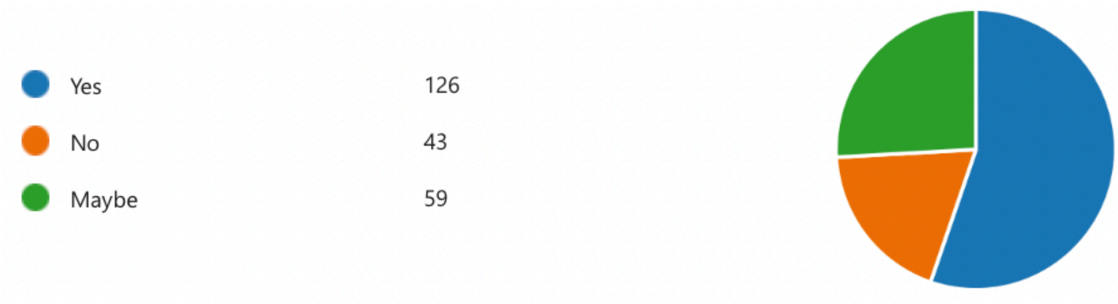


Figure 23: What is stopping you from using a virtual try-on feature? (choose 1 or more options)

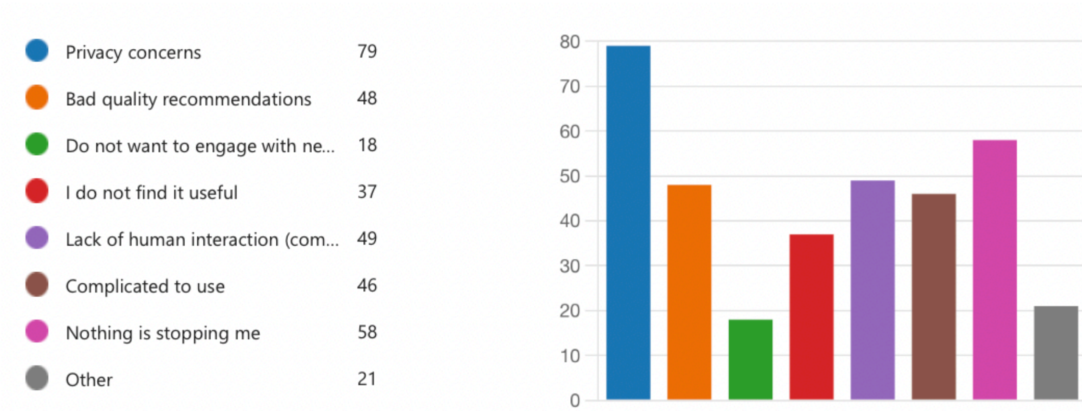


Figure 24: Rate the overall usefulness of using a virtual try-on for a purchase (1 - not at all useful, 5 - very useful)

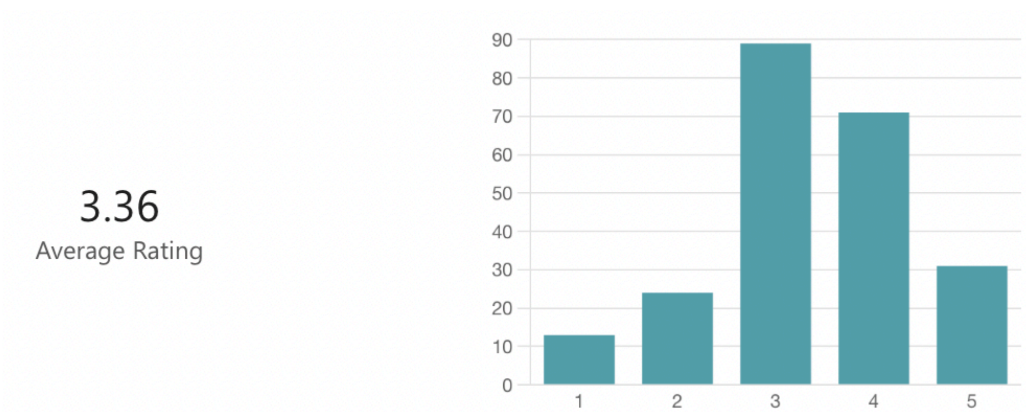


Figure 25: How likely would you share your measurements to a platform using a virtual try-on feature?

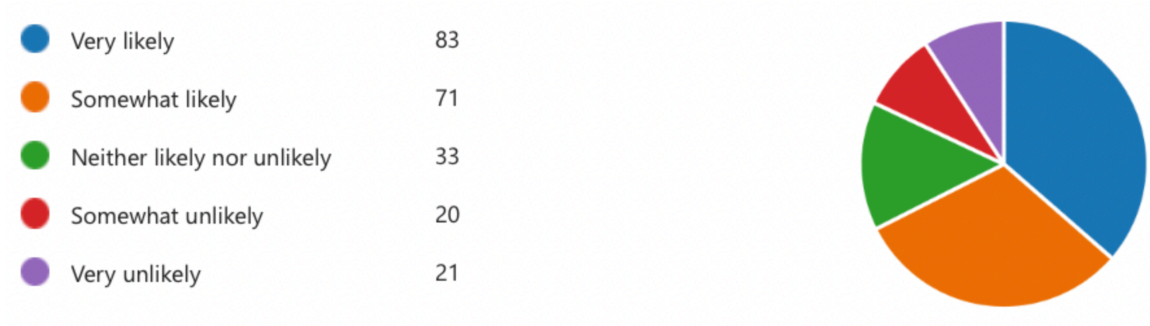


Figure 26: How likely would you upload a photo of yourself to a platform using the virtual try-on feature?

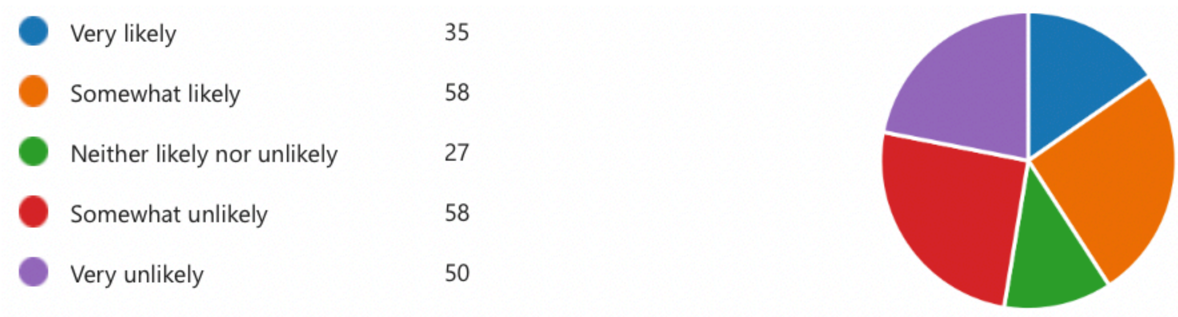


Figure 27: How likely would you record a part of your body to use a virtual try-on feature?

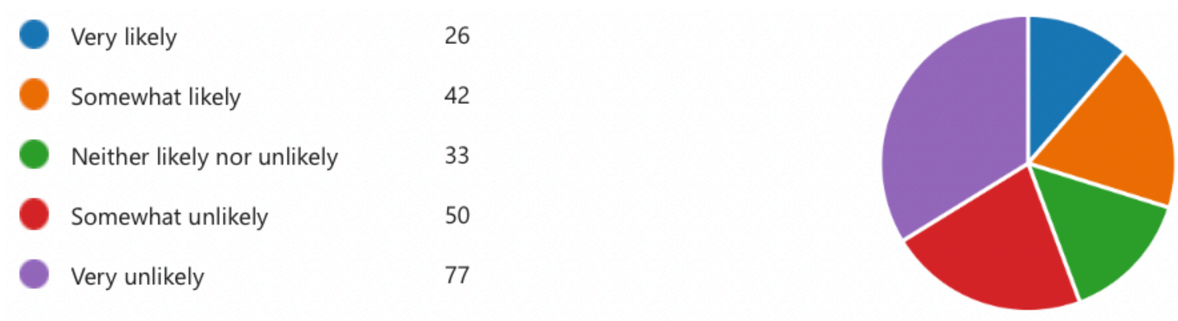


Figure 28: To what extent is distrust in how your data will be processed stopping you from using a virtual try-on feature? (1 - not at all, 5 - very much)

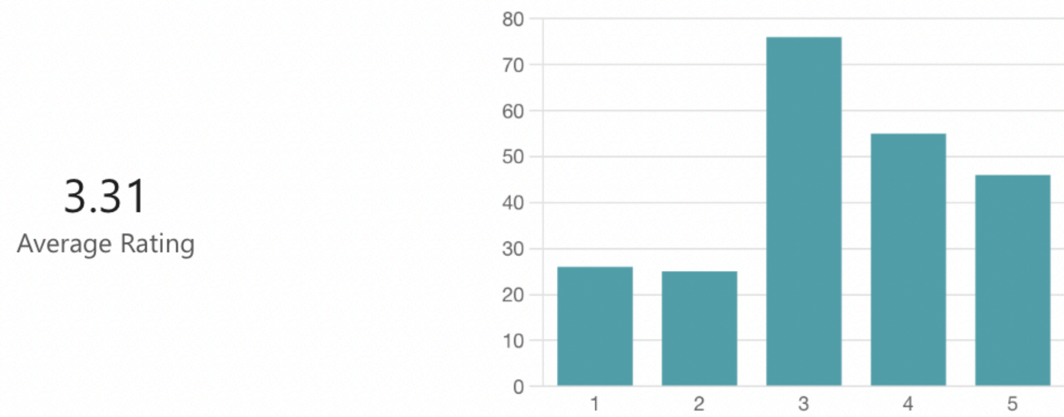


Figure 29: Imagine you want to virtually try-on a new product. Which platform would you feel most comfortable using?

Figure 30: For which product would you more likely accept data privacy terms and conditions, without carefully analysing them? (Choose one or more options)

Figure 31: Ranking list of options: willingness to virtually try on by product

Figure 32: Ranking list of options: usefulness to virtually try on by product

Figure 33: How comfortable are you to virtually try on upper body clothing?

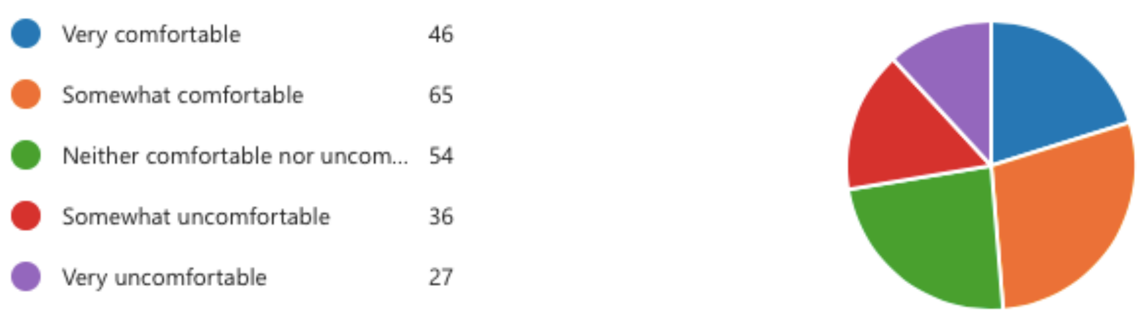


Figure 34: How comfortable are you to virtually try on footwear?

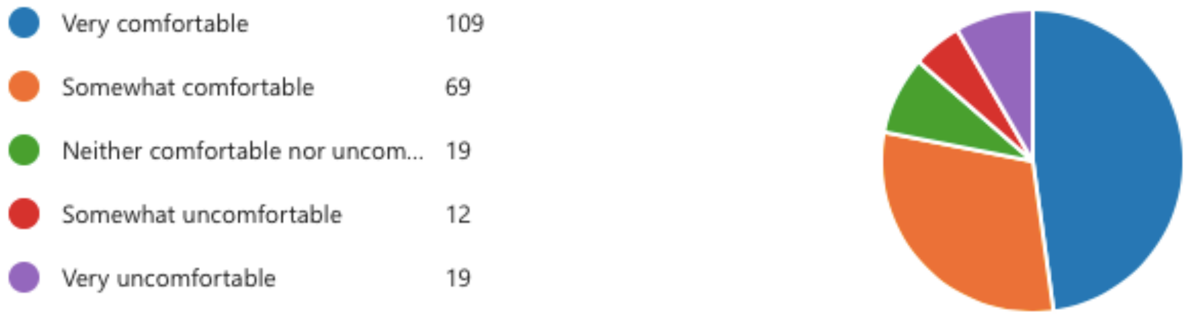


Figure 35: How comfortable are you to virtually try on eyewear?

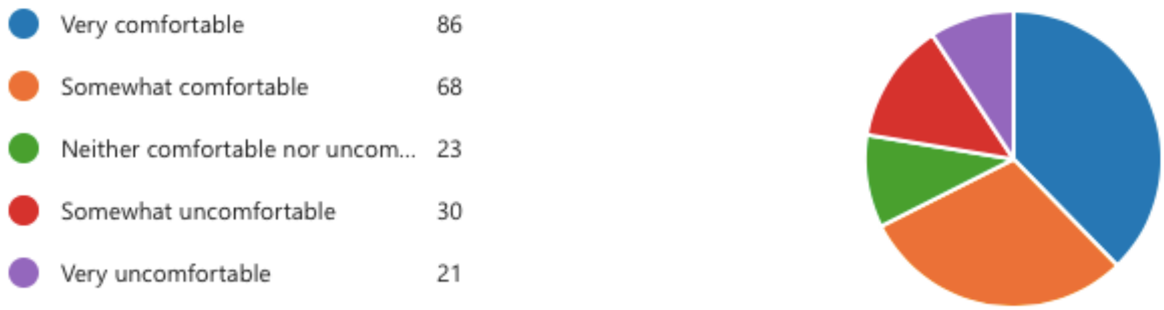


Figure 36: Do you think that virtually trying-on upper garments would help you decide more easily when shopping online?

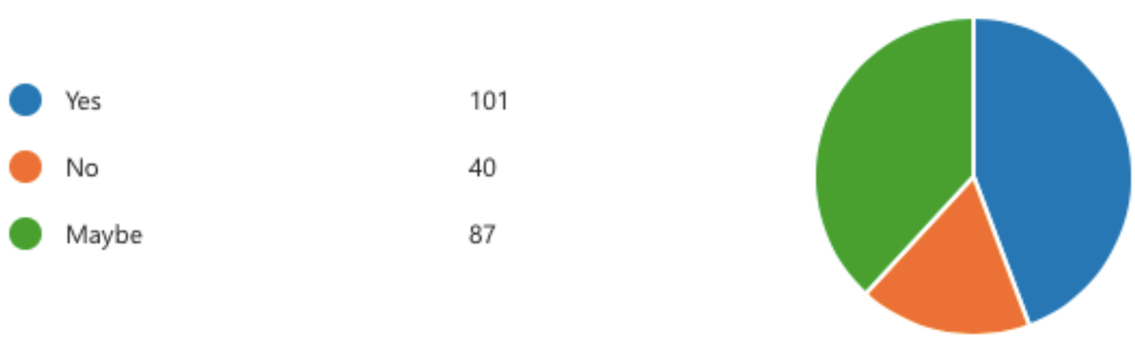


Figure 37: Do you think that virtually trying-on footwear would help you decide more easily when shopping online?

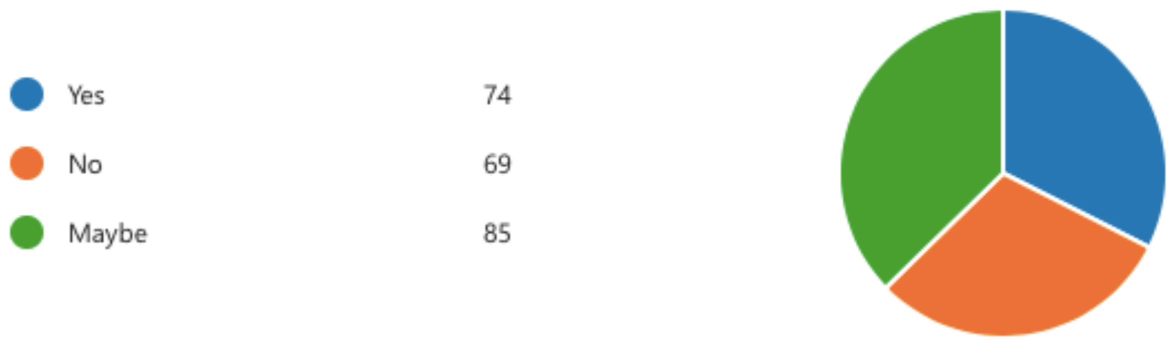


Figure 38: Do you think that virtually trying-on eyewear would help you decide more easily when shopping online?

12.4 Conjoint Analysis

12.4.1 Survey Setup

Table 8: Overview of Attributes and Levels

Attribute	**Levels**	**Source**
1) Product Type	• Upper garments • Footwear • Eyewear	Heller et al. 2019 Zak 2020 Pantano, Rese, and Baier 2017 Hilken et al. 2017 Baek, Yoo, and Yoon 2018 Poushneh 2018 Cowan, Javornik, and Jiang 2021 Eisert, Fechteler, and Rurainsky 2008 Jimeno-Morenilla, Sánchez-Romero, and Salas-Pérez 2013 Hirst and Omar 2007 Merle, Senecal, and St-Onge 2012 Baytar, Chung, and Shin 2020 Ivanov, Mou, and Tawira 2022 Heller et al. 2019 Scholz and Duffy 2018
2) Online Shopping Experience	• Regular online shopping • Personalised online shopping based on shared measurements • Personalised online shopping with an avatar • Personalised Online Shopping with Virtual Try-On	Kim and Forsythe 2009 Lee, Fiore and Kim 2006 Kim and Forsythe 2009 Merle, Senecal, and St-Onge 2012 Ivanov, Mou, and Tawira 2022 Baytar, Chung, and Shin 2020

3) Data Privacy	• Accept mandatory cookies • Accept mandatory cookies, share personal measurements • Accept mandatory cookies, share personal measurements, upload a picture • Accept mandatory cookies, terms & conditions of VTO, give access to camera	Stradivarius 2022 Zara 2022 Farftech 2022 Quay Australia 2022

Table 9: Applicability of levels according to Data Privacy

Applicability of levels according to Data Privacy				
Levels	***Accept mandatory cookies***	***Accept mandatory cookies, share personal measurements***	***Accept mandatory cookies, share personal measurements, upload a picture***	***Accept mandatory cookies, terms & conditions of VTO, give access to camera***
Product Type				
Upper garments	✓	✓	✓	✓
Footwear	✓	✓	✓	✓
Eyewear	✓	✓	✓	✓
Online Shopping Experience				
Regular online shopping	✓			
Personalised online shopping based on shared measurements		✓		
Personalised online shopping with an avatar			✓	
Personalised online shopping with Virtual Try-On				✓

Figure 62: Conjoint Analysis Survey Design Overview

CONJOINT.LY INTRODUCTION

Welcome to this study that allows you to treat yourself with a little retail therapy!

Throughout the survey you will be presented with different cases of online shopping experiences related to different products. You will have to pick the one that suits you the most, based on your needs and preferences. The 4 different online shopping experiences are: **(1) Regular online shopping, (2) Personalised online shopping based on measurements**, where you have to share your body measurements to receive fitting and sizing recommendations**, (3) Personalised online shopping based on avatar**, where you have to take a picture of yourself in order to activate your avatar, and **(4) Personalised online shopping with Virtual Try-On (VTO), where you have to record yourself while you are virtually trying on products. A Virtual try-on (VTO)** refers to trying on digitally created garments or accessories in a virtual environment.
It will require less than 10 minutes of your time. The answers are anonymous and there is no right or wrong answer. We appreciate your participation. Keep calm and shop on!

SECTION 1 – CHOICE OF ONLINE SHOPPING EXPERIENCE

Product Type
- Upper garments
- Footwear
- Eyewear

Data Privacy
- Accept mandatory cookies
- Accept mandatory cookies, share personal measurements
- Accept mandatory cookies, share personal measurements, upload a picture
- Accept mandatory cookies, terms & conditions of VTO, give access to camera

Online Shopping Experience
- Regular online shopping
- Personalized online shopping based on shared measurements
- Personalized online shopping with an avatar
- Personalized Online Shopping with Virtual Try-On

SECTION 2 – ADDITIONAL QUESTIONS

Segment Distributors
- Gender
- Age

Consumer's Perspective
- Would you like to share any other thoughts about this service?

12.4.2. Results

Figure 63: Respondents Gender Distribution

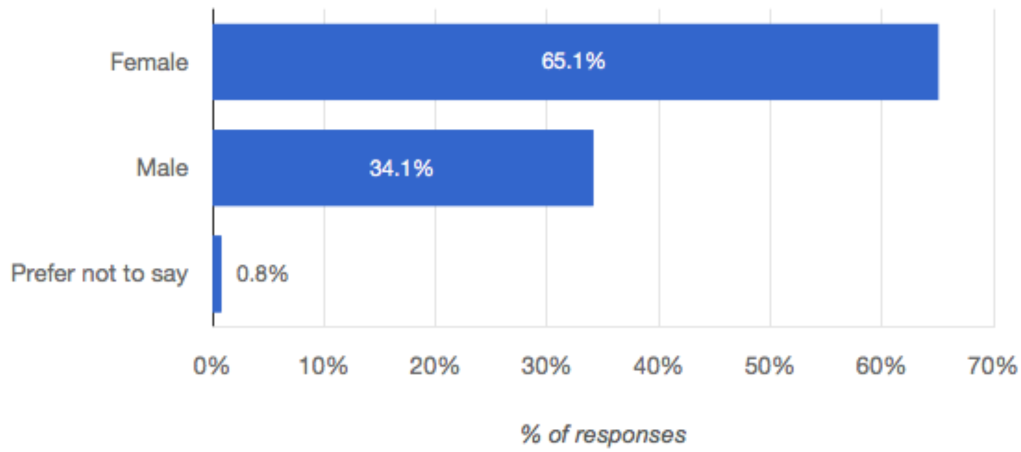


Figure 64: Respondents Age Distribution

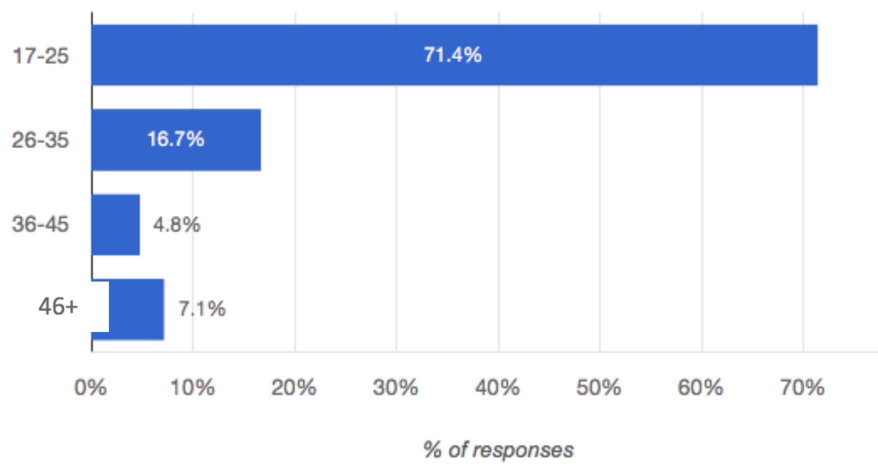


Table 10: Ranked List of Concepts

Rank	Product	Data Sharing	Online shopping experience	Minimum	Median	Maximum
1	**Upper garments**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	8,6	10,9	13
2	**Footwear**	Accept mandatory cookies	Regular	7,8	10,3	13
3	**Upper garments**	Accept mandatory cookies	Regular	5,1	7,5	10
4	**Footwear**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	4,6	6,9	9,4
5	**Eyewear**	Accept mandatory cookies	Regular	0,12	3,7	7,7
6	**Upper garments**	Accept mandatory cookies, terms & conditions VTO, give access to camera	Personalised with VTO	(1,6)	0,9	3,4
7	**Footwear**	Accept mandatory cookies, terms & conditions VTO, give access to camera	Personalised with VTO	(5,6)	(3,0)	(0,46)
8	**Upper garments**	Accept mandatory cookies, share personal measurements, upload a picture	Personalised with avatar	(4,8)	(3,3)	(1,8)
9	**Eyewear**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	(6,3)	(3,9)	(1,4)
10	**Eyewear**	Accept mandatory cookies, terms & conditions VTO, give access to camera	Personalised with VTO	(7,2)	(4,3)	(1,4)
11	**Eyewear**	Accept mandatory cookies, share personal measurements, upload a picture	Personalised with avatar	(8,9)	(6,5)	(4,1)
12	**Footwear**	Accept mandatory cookies, share personal measurements, upload a picture	Personalised with avatar	(23)	(19,2)	(16)

Table 11: Data Privacy/Online Shopping Experience Preference Descriptive Statistics per segment

Experience	Segment	Minimum	Median	Maximum
1	**17-25**	4,6	8,1	11
	26-35	(2,0)	3,7	4,5
	36-45	14,6	15,2	19
	46+	(1,6)	4,6	9,6
	Whole sample	3,7	7,5	10,3
2	**17-25**	(4,0)	6,9	11,6
	26-35	(4,2)	6,9	8,5
	36-45	(6,2)	1,8	5,8
	46+	(1,6)	9,8	14,1
	Whole sample	(3,9)	6,9	10,9
3	**17-25**	(19,3)	(6,8)	(3,3)
	26-35	(15,0)	(3,0)	(1,8)
	36-45	(23,7)	(12,3)	(5,8)
	46+	(23,8)	(5,4)	(4,0)
	Whole sample	(19,2)	(6,5)	(3,3)
4	**17-25**	(5,3)	(3,8)	0,5
	26-35	(0,2)	(0,2)	3
	36-45	(4,1)	(3,5)	(0,7)
	46+	(4,1)	(1,2)	3,7
	Whole sample	(4,3)	(3,0)	0,9

Table 12: Ranked list of concepts per segment

Segment	Rank	Product	Data Sharing	Online shopping experience	Minimum	Mean	Maximum
17-25	1	**Upper garments**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	8,8	11,56	14,4
	2	**Footwear**	Accept mandatory cookies	Regular	7,6	11,00	14,4
	3	**Upper garments**	Accept mandatory cookies	Regular	4,8	8,08	11,3
26-35	1	**Upper garments**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	4,7	8,49	12,2
	2	**Footwear**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	2,5	6,85	10,9
	3	**Footwear**	Accept mandatory cookies	Regular	(0,5)	4,45	9,6
36-45	1	**Footwear**	Accept mandatory cookies	Regular	-	19,01	-
	2	**Eyewear**	Accept mandatory cookies	Regular	-	15,22	-
	3	**Upper garments**	Accept mandatory cookies	Regular	-	14,55	-
>45	1	**Upper garments**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	-	14,09	-
	2	**Footwear**	Accept mandatory cookies, share personal measurements	Personalised with shared measurements	-	9,76	-
	3	**Footwear**	Accept mandatory cookies	Regular	-	9,55	-

Table 13: Partworth utilities of all the experiences per segment – Product Type

Experience	Segment	Upper garments	Footwear	Eyewear
1	**17-25**	3,1%	48,5%	(51,6%)
	26-35	25,40%	37,3%	(62,7%)
	36-45	(38,30%)	61,7%	(23,4%)
	46+	3,8%	48,1%	(51,9%)
	Whole sample	5,6%	47,2%	(52,8%)
2	**17-25**	43,3%	13,5%	(56,8%)
	26-35	37,6%	24,7%	(62,3%)
	36-45	44,3%	11,4%	(55,7%)
	46+	42,5%	14,9%	(57,4%)
	Whole sample	42,3%	15,4%	(57,7%)
3	**17-25**	40,6%	(59,5%)	18,9%
	26-35	36,5%	(63,4%)	26,9%
	36-45	45,6%	(54,5%)	8,9%
	46+	35,7%	(64,3%)	28,6%
	Whole sample	40,0%	(60,0%)	20,0%
4	**17-25**	57,9%	(15,8%)	(42,1%)
	26-35	66,1%	(32,2%)	(33,9%)
	36-45	61,5%	(22,9%)	(38,6%)
	46+	54,4%	(8,7%)	(45,7%)
	Whole sample	58,5%	(17,1%)	(41,4%)

12.5 Clustering: Consumer Segments

12.5.1 Clustering Setup

Table 14: Conversion from nominal to numerical values in IBM SPSS

Question	Nominal Value	Numerical Value
1. How often do you use a virtual try-on feature when shopping online for fashion products?	Never	1
	Occasionally	2
	Sometimes	3
	Seasonally	4
	Often	5
15., 17., 19. How comfortable do you feel to virtually try-on upper body clothing/eyewear/footwear?	Very uncomfortable	1
	Somewhat uncomfortable	2
	Neither comfortable nor uncomfortable	3
	Somewhat comfortable	4
	Very comfortable	5
21. What is your gender?	Male	1
	Female	2

	Prefer not to say	3
22. How old are you?	17-25	1
	26-35	2
	36-45	3
	46+	4
24. How often do you shop online?	Never	1
	Occasionally	2
	Yearly	3
	Seasonally	4
	Monthly	5
	Weekly	6
	Daily	7

Figure 65: Python code for Scree Plot: Elbow Method

```
#Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn import datasets
from yellowbrick.cluster import KElbowVisualizer
plt.figure(figsize=(12,8))

#Importing data
df = pd.read_excel('clusters.xlsx')

#Kmeans model
model = KMeans()

#Elbow method
visualizer = KElbowVisualizer(model, k=(2,14), timings=False)

#Fit data to visualizer
visualizer.fit(df)

plt.rcParams['font.size'] = 18

#Finalise and render figure
visualizer.show()
```

12.5.2 Results

Figure 66: Number of cases in each cluster – SPSS Output

Number of Cases in each Cluster

Cluster	1	19.000
	2	23.000
	3	63.000
	4	70.000
	5	28.000
	6	25.000
Valid		228.000
Missing		.000

Figure 67: Final Cluster Centers – SPSS Output

Final Cluster Centers

	Cluster					
	1	2	3	4	5	6
Usefulness of VTO	2.84	2.35	3.00	3.94	4.25	2.92
Distrust in Data Privacy	3.63	4.52	3.92	2.60	2.75	3.00
Comfortability VTO upper garments	3.74	1.22	2.41	4.29	4.36	3.12
Comfortability VTO footwear	4.79	1.65	4.11	4.71	4.79	2.80
Comfortability VTO eyewear	3.89	1.48	3.40	4.60	4.82	2.92
Frequency of Online Shopping	2.95	2.13	3.75	3.91	5.57	4.72
Age	4	3	1	1	2	2

Figure 68: ANOVA – SPSS Output

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Usefulness of VTO	17.524	5	.714	222	24.528	<.001
Distrust in Data Privacy	21.139	5	1.085	222	19.488	<.001
Comfortability VTO upper garments	50.618	5	.542	222	93.471	<.001
Comfortability VTO footwear	45.593	5	.539	222	84.631	<.001
Comfortability VTO eyewear	45.371	5	.790	222	57.440	<.001
Frequency of Online Shopping	37.161	5	1.013	222	36.686	<.001
Age	34.995	5	.510	222	68.588	<.001

The F tests should be used only for descriptive purposes because the clusters have been chosen to maximize the differences among cases in different clusters. The observed significance levels are not corrected for this and thus cannot be interpreted as tests of the hypothesis that the cluster means are equal.

Figure 69: Final Cluster Centers bar graph

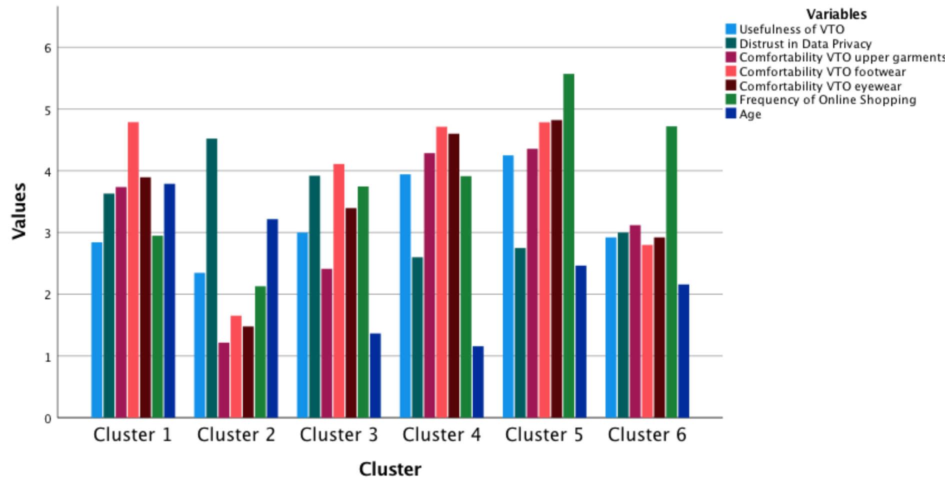


Figure 70: Cluster 1 characteristics

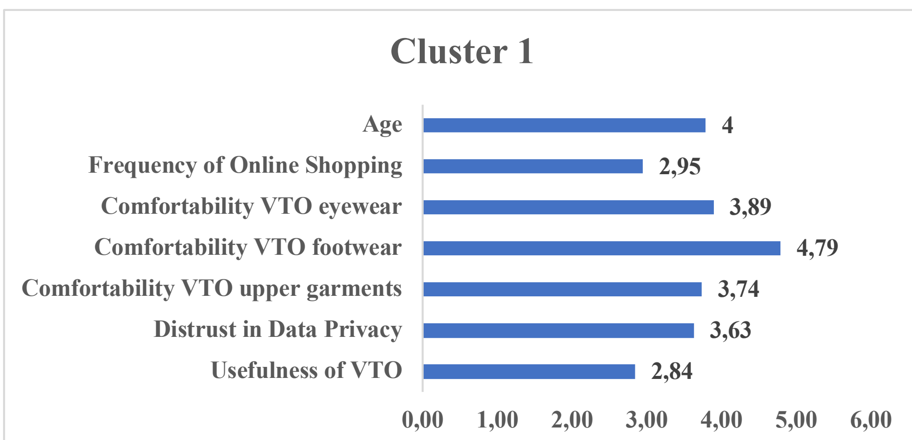


Figure 71: Cluster 2 characteristics

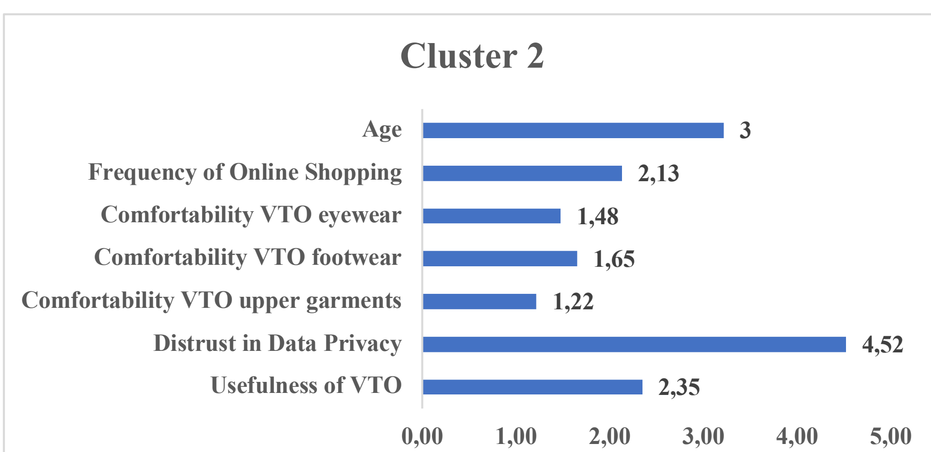


Figure 72: Cluster 3 characteristics

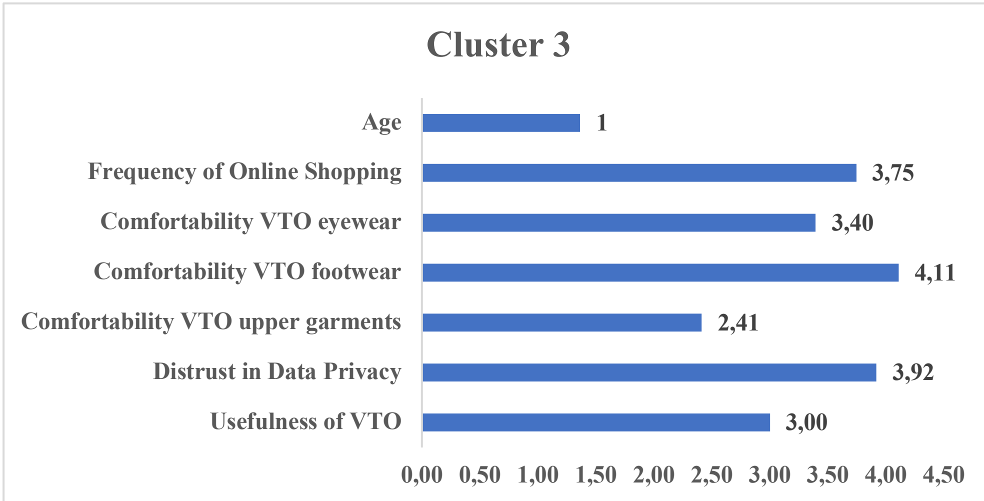


Figure 73: Cluster 4 characteristics

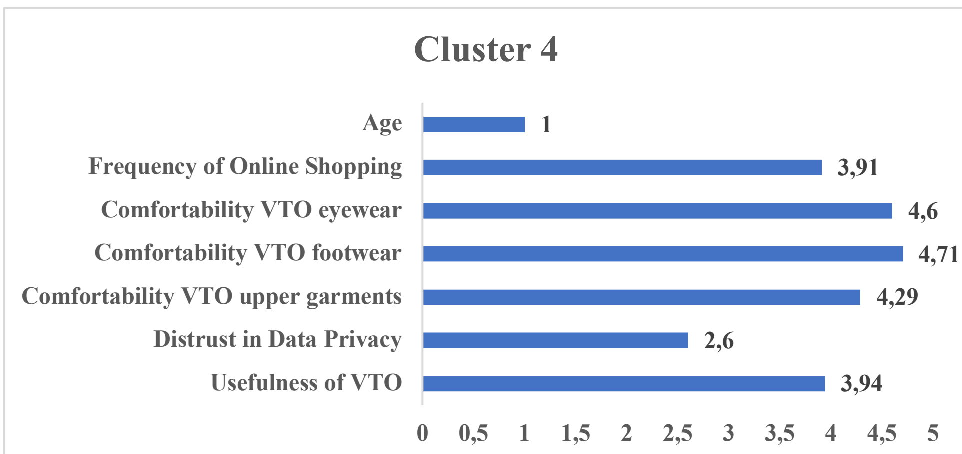


Figure 74: Cluster 5 characteristics

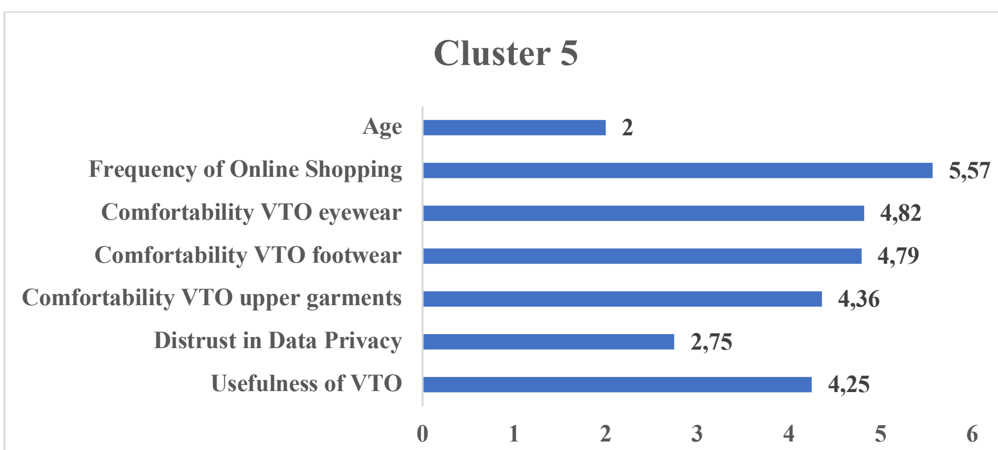
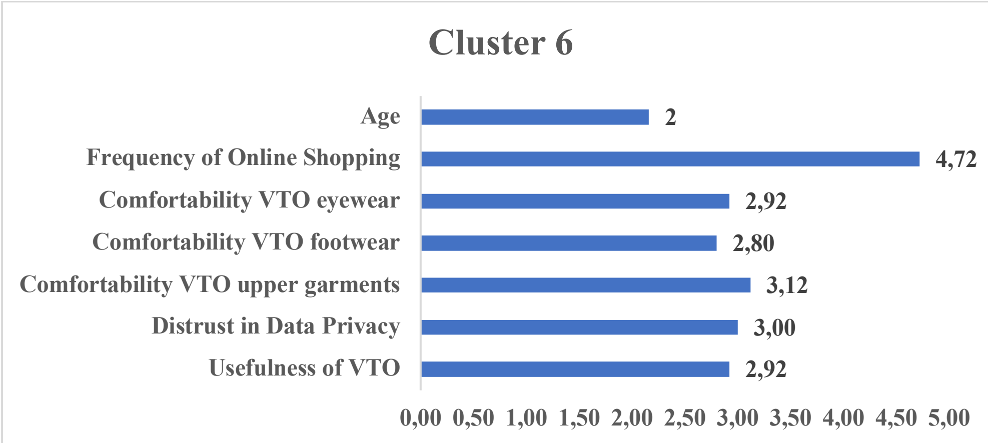


Figure 75: Cluster 6 characteristics



12.6 Conjoint Analysis: Recommendations for VTO for Eyewear

12.6.1 Survey Setup

Table 15: Overview of Attributes and Levels

Attribute	Levels	Source
1) Type of VTO	• Personalised avatar based on measurements and picture • VTO recording of yourself	Lee, Fiore, and Kim 2006 Kim and Forsythe 2009 Merle, Senecal, and St-Onge 2012 Ivanov, Mou, and Tawira 2022 Baytar, Chung, and Shin 2020
2) Where to use VTO	• Mobile application • Brand's website • Social Media Filters (Snapchat/Instagram)	Feng and Xie 2018 Harborth and Pape 2021 Cowan, Javornik, and Jiang 2021
3) Purpose of experience	• Fun and interactivity • Picking the right product (size/fit)	Watson, Alexander and Salavati 2018 Hwangbo et al. 2020 De Canio, Fuentes-Blasco, and Martinelli 2021 Yim, Chu, and Sauer 2017 Yang and Wu 2009 Lee, Xu and Porterfield 2022 Baytar, Chung, and Shin 2020 Rese et al. 2017

Figure 76: Conjoint Analysis Survey Design Overview

CONJOINT.LY INTRODUCTION

Hello, help us finish our Master's Thesis by filling out this survey :) It will take 3 to 5 minutes, and your help is very much appreciated. The survey is anonymous, and there are no right or wrong answers.
Before you start, a Virtual Try-On (VTO) refers to how a customer can "try on" a product through mobile or other devices.

There are 2 types of VTOs:
1) **VTO recording of yourself,** for which you need to **accept mandatory cookies, terms & conditions of the VTO, and give access to the camera**.
2) **Personalized avatar based on measurements and picture**, for which you need to **share body measurements and upload a photo of your face**.

SECTION 1 – CONFIMRATION OF DATA AWARENESS

Please confirm you are aware you need to accept mandatory cookies, terms & conditions of VTO, and give access to camera when VTO recording yourself

Please confirm you are aware you need to accept mandatory cookies, share personal measurements, and upload a picture of your face in order to engage with a personalized avatar

SECTION2 – CHOICE OF ONLINE SHOPPING EXPERIENCE

Type of VTO
- **VTO recording of yourself**
- **Personalized avatar based on measurements and pictures**

Where to use VTO
- **Mobile application**
- **Brand's website**
- **Social Media Filters**

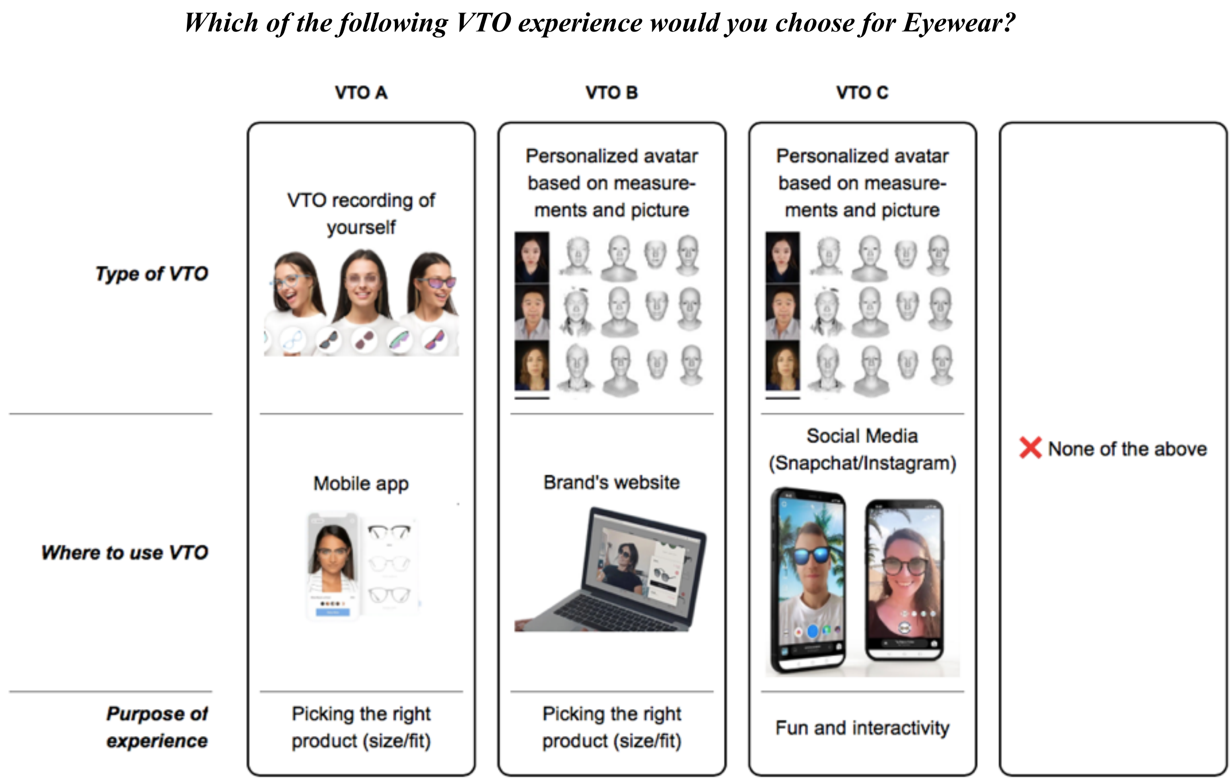
Online Shopping Experience
- **Picking the right product (size/fit)**
- **Fun and interactivity**

SECTION 3 – ADDITIONAL QUESTIONS

For which experience do you believe that the benefits of a personalized shopping experience outweigh the costs of data disclosure? (both; personalized avatar based on measurements and pictures; VTO recording of yourself; none)

Segment Distributors
- **Gender**
- **Age**
- **Self-esteem**
- **Frequency of online shopping**

Figure 77: Layout of the choice sets within Conjoint.ly



12.6.2 Results

Figure 78: Respondents Gender Distribution

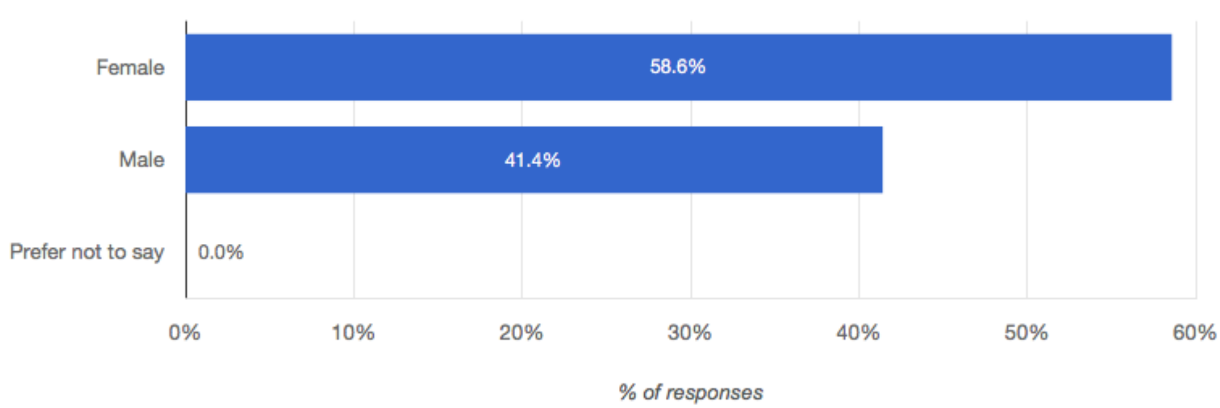


Figure 79: Respondents Age Distribution

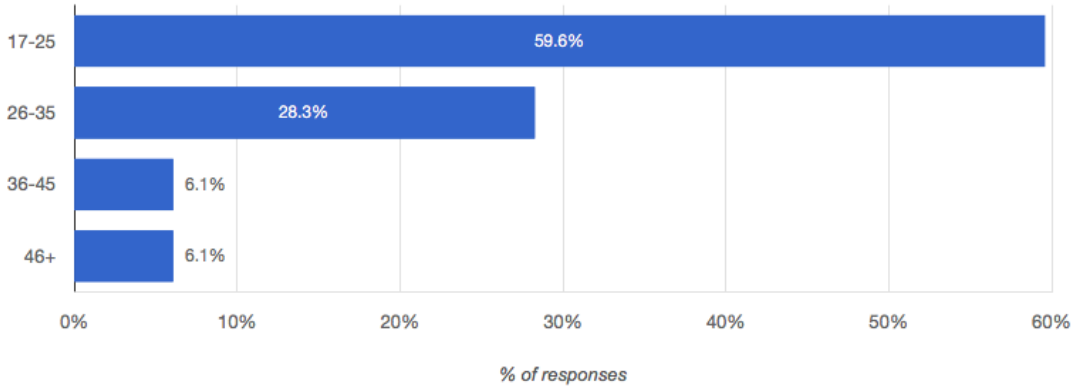


Figure 80: Which personalised experience assures a positive trade-ff between data sharing and added value to the online shopping experience

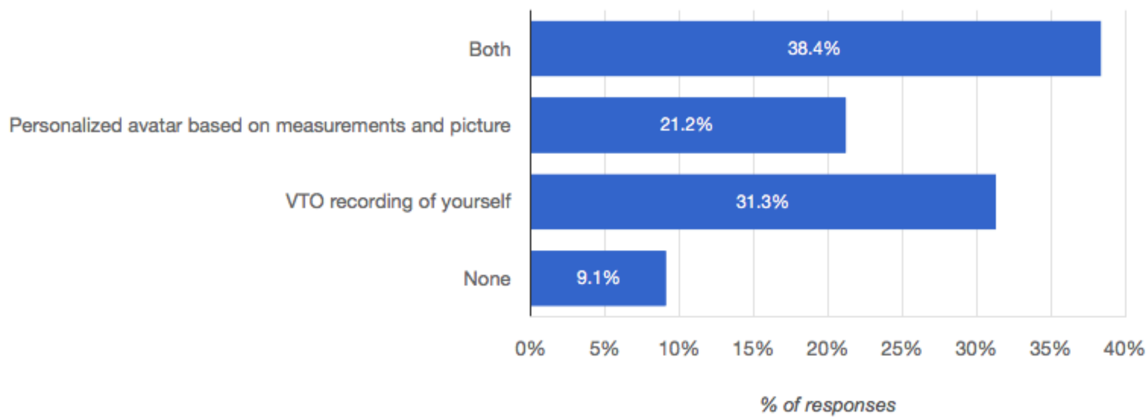


Figure 81: Respondents Distribution of self-esteem ratings

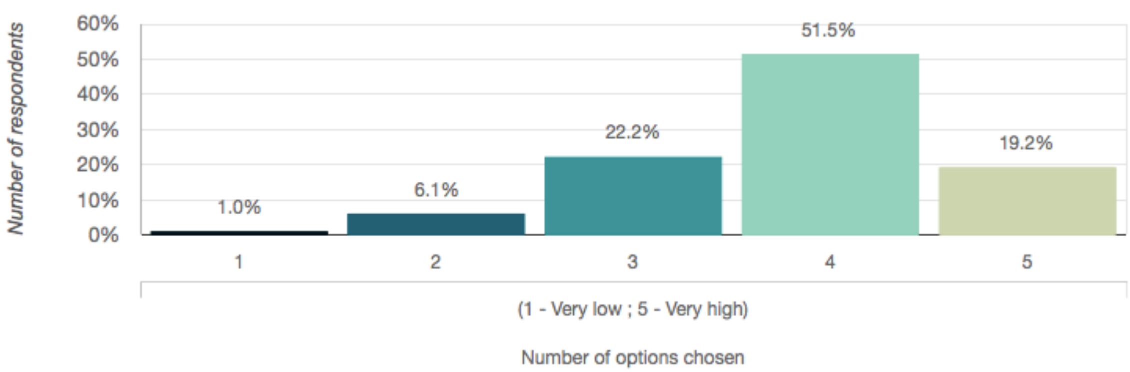


Figure 82: Respondents Distribution of online shopping frequency

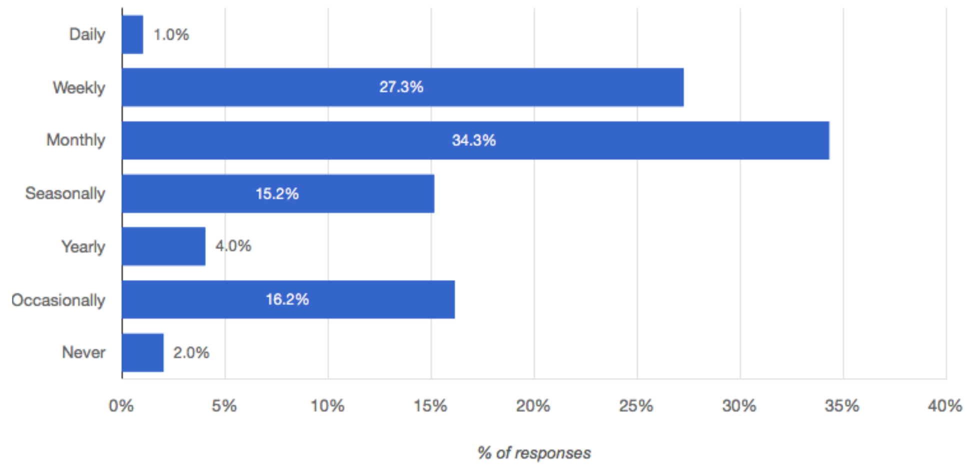


Figure 83: Relative Importance by Attribute

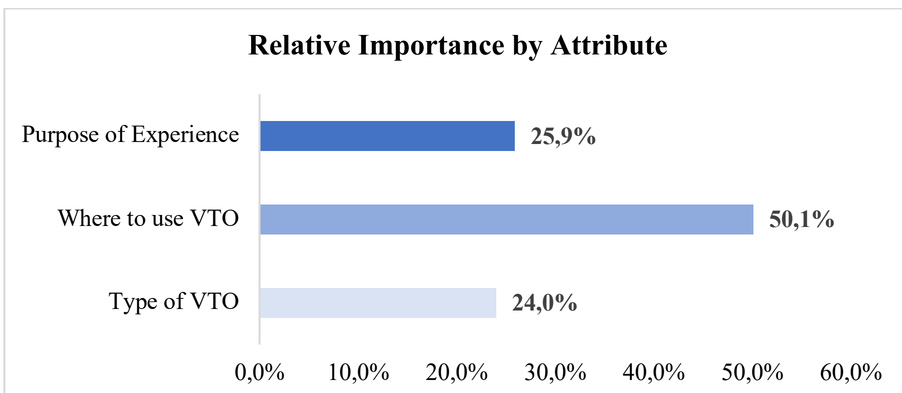


Figure 84: Distribution of preferences for levels by Attribute

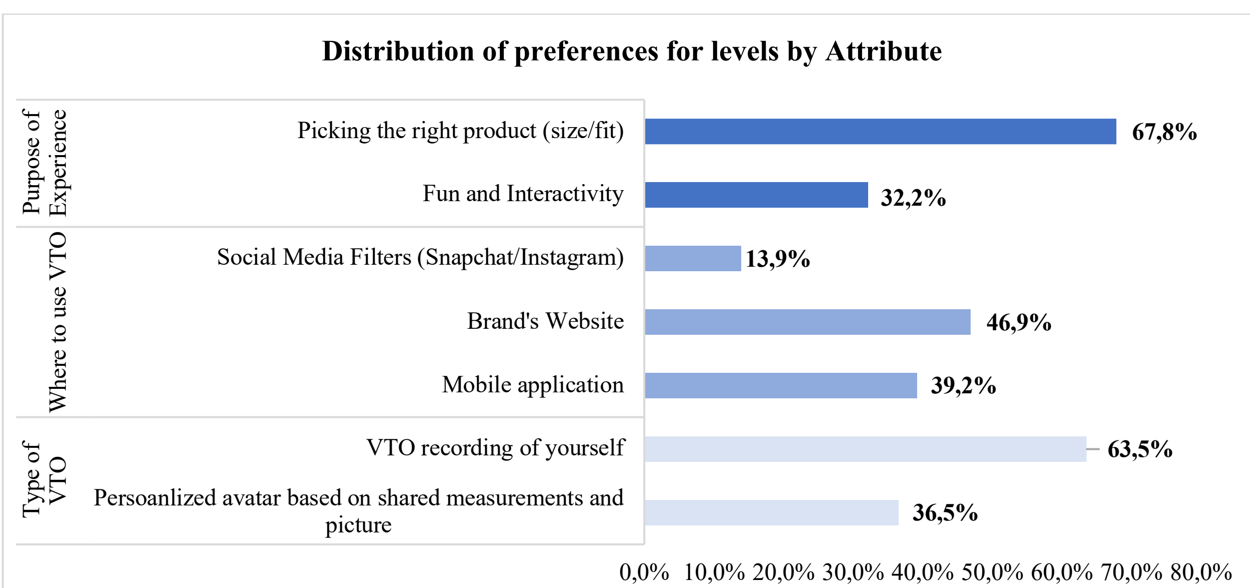


Table 16: Ranked List of Concepts

Rank	Type of VTO	Where to use VTO	Purpose of experience	Minimum	Mean	Maximum
1	**VTO recording of yourself**	Brand's website	Picking the right product (size/fit)	15,9	**20,12**	24,3
2	**VTO recording of yourself**	Mobile application	Picking the right product (size/fit)	15,6	**18,50**	21,7
3	**Personalised avatar based on measurements and picture**	Brand's website	Picking the right product (size/fit)	6,6	**11,52**	16,6
4	**Personalised avatar based on measurements and picture**	Mobile application	Picking the right product (size/fit)	5,5	**9,89**	14,6
5	**VTO recording of yourself**	Brand's website	Fun and interactivity	3,5	**6,91**	10
6	**VTO recording of yourself**	Mobile application	Fun and interactivity	2,6	**5,29**	8
7	**Personalised avatar based on measurements and picture**	Brand's website	Fun and interactivity	(4,4)	**(1,69)**	1
8	**Personalised avatar based on measurements and picture**	Mobile application	Fun and interactivity	(6,1)	**(3,32)**	(0,2)
9	**VTO recording of yourself**	Social Media Filters (Snapchat/Instagram)	Picking the right product (size/fit)	(9,3)	**(5,90)**	(2,4)
10	**Personalised avatar based on measurements and picture**	Social Media Filters (Snapchat/Instagram)	Picking the right product (size/fit)	(17,3)	**(14,51)**	(11,5)
11	**VTO recording of yourself**	Social Media Filters (Snapchat/Instagram)	Fun and interactivity	(25,3)	**(19,11)**	(13,2)
12	**Personalised avatar based on measurements and picture**	Social Media Filters (Snapchat/Instagram)	Fun and interactivity	(32,6)	**(27,72)**	(23,1)