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ONLINE CLOTHING RESELLING PLATFORMS: PERCEPTIONS AND PREFERENCES OF ITALIAN CONSUMERS

Attribute preferences on clothing reselling platforms of Italian Consumers — Impact of different attribute levels on platform adoption

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Abstract – Group Part

The research focuses on second-hand fashion platforms (Vinted, Vestiaire Collective, Depop, Zalando Second-hand) in Italy from a consumer standpoint. The study assesses the platform's positioning, and most preferred characteristics, as well as the potential consumer segments in the Italian market. By conducting surveys with consumers, and applying market research techniques such as perceptual maps, conjoint analysis, and k-means clustering, we were able to learn about consumers' perceptions, preferences, and their relevance to the platforms. The main discoveries are then used to suggest recommendations for the companies to improve their market presence and competitive edge.

Abstract – Individual Part

The individual part is taken out of the conjoint analysis and is comprised of counterfactual scenarios, which have been conducted to allow further insights into consumer preferences, especially into price sensitivity. For this purpose, starting with the attribute composition of the most realistic market scenario, scenarios have been created for the most important attributes of the conjoint study: buyer protection, product price and additional fee. The analysis of the different scenarios enabled the finding that price sensitivity does depend on the brand on the one hand and on the type of monetary component, i.e. product price and additional fee.

Keywords: Market Research, Perceptual Maps, Conjoint Analysis, K-Means Clustering, Clothing Reselling Platforms, Consumer Insights

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Table of Contents

1 Group Part

1.1 Introduction

The world moving from physical to digital has and is disrupting the way we interact and consume. This has given rise to new business models and has accelerated the development of whole new industries and market players. The fashion industry has not remained untouched by this phenomenon. As part of this industry, the secondhand market has been severely impacted as well. Indeed, the digital shift determined the rise of second-hand fashion platforms, allowing consumers to sell and buy secondhand clothing more easily (McKinsey 2020).

This transition to online markets is also accompanied by other trends gravitating around the online second-hand market growth. Firstly, sharing economy models had a tremendous growth in the last ten years, and this willingness to share has impacted the fashion industry as well. Indeed, this new consumption model determined the uprising of second-hand online platforms as part of the sharing economy phenomenon (Netter and Pedersen 2019). Secondly, due to the increasing awareness towards environmental problems, more and more consumers started considering the purchase of second-hand items as a more sustainable alternative to buying new items . Thirdly, also due to a trend towards vintage clothing, the number of consumers buying second-hand clothes has been rising tremendously (Cassidy and Bennett 2012; Ryding, Henninger and Blazquez Cano 2018). These developments most likely explain why the second-hand clothing market, with a current value of 27 billion U.S. dollars, is forecasted to reach a value of 84 billion U.S. dollars by 2030, surpassing the one of the fast fashion markets (Statista 2021a; Statista 2021b).

Due to the market dynamics being impacted by multiple phenomena, there has been an increased research interest in consumer behavior specifically from both an academic and business perspective (Willersdorf, et al. 2020; Abbes, Hallem and Taga 2020). The development of a whole new industry with new players, accelerated by a shift in consumer patterns, have motivated us to investigate the perceptions and preferences of Italian consumers about the secondhand fashion market and its players. Italy was chosen as the market of interest because of several reasons. Besides its traditional influence on the fashion industry (Paulicelli 2014; Statista 2021c), Italy has the second highest spending on clothing and apparel in the EU per capita and represents one of the core markets for relevant online platforms such as Depop and Vinted (Statista 2020a; Statista 2021d; Statista 2021g; Statista 2018a).

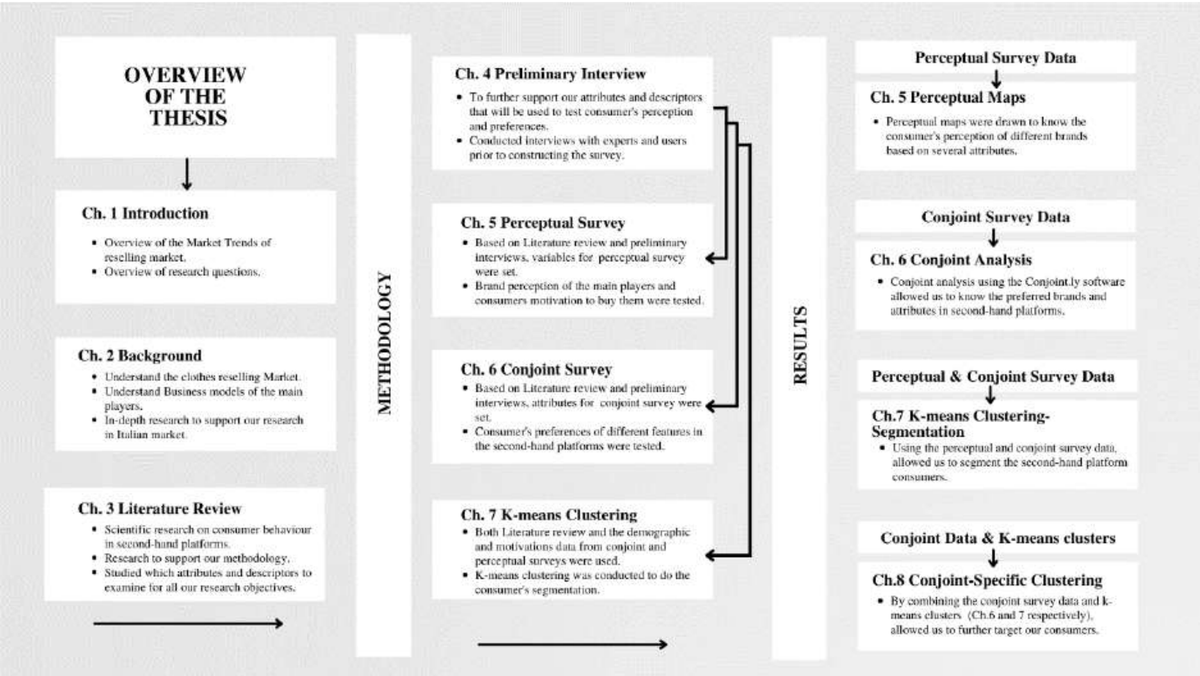
In this context, looking at the Italian market directly, the largest players are comprised of C2C and B2C platforms, which were chosen as players to investigate. Along with this distinction goes, that looking at the C2C platforms more specifically, consumers might be buyers or sellers or both, as opposed to the B2C platforms. Therefore, in order to provide consistent findings, our thesis will only take the buyer perspective into account.

This thesis will address the following research questions:

1) How do Italian consumers perceive the different main players and how are these brands positioned in the market?
2) Which app attributes and brands are most valued by Italian consumers and how can the major market players improve their platform performance?
3) What are the relevant consumer segments purchasing on second-hand platforms?
4) How do preferences differ across consumer segments?

The study methodology was chosen in order to provide answers to the outlined research questions and can be summarised as follows. For the analysis of the perceptions of Italian consumers of the main market players, the method of perceptual maps was chosen, enabling a visual understanding of the perceptions and positionings of the examined brands in the market. In addition, in order to identify and analyse the app attributes and brands valued by Italian consumers, a choice-based conjoint analysis was chosen due the method's high degree of transferability of the results into reality. Further, the k-means clustering algorithm was applied in order to identify relevant consumer segments for the market of second-hand platforms. Lastly, to answer the fourth research question, a conjoint analysis has been conducted based on the segments identified through the segmentation. The data basis for all methods was provided through the conduct of preliminary interviews and one survey for perceptual maps and conjoint analysis each.

Figure 1: Overview Structure of the Thesis



Providing a more detailed understanding of the structure of the thesis, an overview of the chapters will be provided in the following, supported by Figure 1 above, which illustrates the connections between the chapters.

1) An introduction to the topic from a more general market perspective is provided through chapter 2 on the background. Besides creating an understanding on the market and its development in general, it provides insights into the business models of the market players studied, which serve as foundation for the setup of the conjoint and perceptual analysis.

2) In chapter 3, a literature overview is presented. It examines the existing scientific literature on studies conducted around consumer behaviour related to the second-hand market. The overview supported the outline of the preliminary interviews, the perceptual maps, the conjoint analysis, and the segmentation. More specifically, it allowed us to scope the study, assess which platform perceptions and attributes to examine as well as the descriptors to consider for the consumer segmentation. In addition, it provided the relevant scientific background on the methodologies used in the thesis.
3) In chapter 4, some preliminary qualitative interviews were conducted as a second step of the overall analysis. This allowed us to assess and verify the aspects identified in the literature review within the research of consumer perceptions, preferences, and segmentation. Providing a holistic perspective, the interviews were conducted with both industry experts and consumers. As result, we retained the characteristics and features that were most pertinent to the research and to consumers perceptions and needs.
4) As described in chapter 5, after scoping the research from a literature and qualitative perspective, the perceptual maps surveys were designed and launched. By asking the consumers about their brand perceptions, it was then possible to plot a perceptual map showing the different brands positionings. The survey also contained questions on demographical and motivational factors. This then allowed to perform the consumer segmentation analysis discussed in chapter 7.
5) In chapter 6, following the literature and qualitative interviews discoveries, a choice-based conjoint analysis was designed and conducted. This allowed us to identify consumer preferences, i.e., the partworth utilities of attributes and attribute levels. In a subsequent step, counterfactual scenarios were developed allowing additional insights into market dynamics. Like in the perceptual maps survey design, consumers were also asked about demographic and motivational factors besides the choice-based conjoint

questions. This allowed to later conduct a segmentation analysis, as discussed in chapter 7.

6) In chapter 7, based on the demographic and motivational data obtained through the perceptual and conjoint surveys in the previous chapters, we performed an ex-post segmentation using the k-means clustering algorithm and provided consumer clusters.
7) Chapter 8 combines chapters 6 and 7 through the conduct of a cluster-specific conjoint analysis. The chapter allowed us to verify the applicability and usefulness of the segments identified in chapter 7 and provide strategic implications for which consumers to target.

Having provided an overview of the thesis structure, the results obtained can be highlighted as follows.

By plotting a perceptual map, it was possible to highlight the four players positioning in the online fashion reselling market. It emerged that Vinted is identified as the price leader, along with the most positive associations with sense of community, fun and entertainment. Whereas Vestiaire Collective and Zalando Second Hand have been closely linked to design and style, platform reliability, items quality, service quality and sophistication. Lastly, Depop was found to be the most negatively perceived platform, underscoring competitors' performance on all the attributes tested.

With regards to consumer preferences investigated through conjoint analysis, we found out, that buyer protection, product price and additional fee are the most important attributes, when considering a secondhand platform. However, some variables were not given much importance by the respondents such as delivery services, payment options and the type of variety. With regards to the attribute level preferences, it can be summarized that the overall willingness to pay for both item price and additional fees are rather low, yet, the most preferred item prices depend on the platform. As such, the most preferred price for Vinted were 5€, for Zalando Second Hand 15€, for Vestiaire Collective and Depop 30€. This points to a certain degree of brand loyalty and price signaling quality. For additional fee, the most preferred attribute was “Free”, however some preference was also for “2,99€”. Surprisingly, all elasticities, for item price and additional fee have been found to be inelastic allowing some leeway in pricing for the platforms.

An additional result obtained from the different methodology techniques applied in this study, was concerning the motivations when it comes to purchasing actions through second-hand clothes by means of the previously mentioned platforms. Where in both outcomes from the samples for perceptual maps and conjoint analysis, it was shown the significant influence that the sustainable purchase philosophy has on some user segments.

The ex-post segmentation revealed four possible consumer segments: (i) the fashionistas, mid-income under-35 women, mainly driven by the coolness and uniqueness of the items in the second-hand market as well as the possibility of buying designer and luxury items; (ii) the bargain hunters, mid-income men and women merely looking for a money-saving escape in the second-hand fashion market, uninterested in fashion or sustainability; (iii) the connoisseurs, 35+ women with higher frequency of purchase and higher income, buying second-hand for the price/quality ratio, the uniqueness and coolness of the items and the possibility of buying luxury and designers items; (iv) the sustainable youngsters, 16-25 aged men and women, lower income spenders, buying second-hand for its price-quality ratio and its sustainable impact.

Applying the previously identified clusters on conjoint, some clear differences especially with regard to the attribute importance of item price, buyer protection and additional fee could be detected. In addition, the clusters clearly differed in their willingness to pay regarding the item price.

After briefly introducing the market, the methodologies used, the thesis structure and giving a brief outlook of the results, the following chapter will provide an understanding of the market and its players in depth.

1.2 Background

To shed some light on the overall topic, the following chapter will introduce the overall market with its landscape and its players. This analysis represents an important step in order to assess the relevance of the topic chosen, the specific market selected as well as the selected market players.

1.2.1 Global Market Growth and the Italian Market Landscape

In 2019, the pre-owned clothing industry in the US generated a value of 28 billion dollars. Indeed, it is supposed to reach 84 billion U.S. dollars - double of fast fashion (40 billion U.S. Dollars) - by the year 2030 (Statista 2021b). It is also forecasted that for the five-year period between 2019 and 2024 the resale second-hand segment will experience a growth of 414% compared to 34% in the traditional segment in the world. These figures are particularly significant when compared to a 4% decrease expected for the entire retail segment of the fashion industry (ThredUp 2022).

The paradigm shift represented by pre-owned fashion is the result of a change in consumer purchasing habits and preferences. The image and perceptions towards the second-hand market have undergone a profound metamorphosis: second-hand garments are no longer purchased only by people with limited financial resources or by niches interested in vintage clothing. The emergence of instances of critical consumption and the consequent adoption of conscious behaviour by consumers lead the latter to move away from alternative fashion, but from a wider and more varied audience. The extent of this phenomenon is particularly relevant if analysed in the context of the fashion industry, in which the debate is currently focused on issues such as environmental and social sustainability of the current production model (McKinsey 2020).

In this context, Italy seems to be an interesting market to study. Starting from Renaissance, Italy has been building a long history of fabric, textile culture and fashion savoir-faire.

However, just after the second-world war, the country started gaining ground, getting the deserved international recognition, competing with the already existing French fashion (Paulicelli 2014). Today, Italy is ranked as the second most leading fashion country in the world after France (Statista 2021c). Regarding second-hand, Italy displayed a consistent growth in the last decade. A study conducted by BVA Doxa (2021) estimates that in the five-year period 2014-2019 the second-hand industry in Italy grew by 33%. The extent of this phenomenon is also evidenced by the turnover generated: in 2019 the second-hand market reached the value of 24 billion euros, an increase of 55% compared to the previous year. Similarly, the pre-owned fashion market in Italy today has a value of 1.3% of the national GDP.

Digital has played and plays a key role in the development of the second-hand market: it is estimated that the online segment in Italy in 2019 generated a turnover of 10.5 billion euros, equal to 45% of the total industry sales. In the same year, 58% of consumers in this segment turned to the online channel, preferring it to the traditional channel. This trend increased during the pandemic: during 2020, 77% of buyers and 81% of sellers turned to the online channel.

The main reasons that induced consumers to turn to the second-hand garment segment are of different nature: 59% of respondents are driven by the desire to save money, 51% by the desire to find unique or vintage items and 48% are driven by sensitivity towards sustainability issues such as recycling and product reuse. Furthermore, the prospects of the Italian pre-owned market are rosy: 71% of the Italians believe that the sector is going to grow in the next five years as a sustainable consumption choice (48%), as it represents an excellent way to save money (47%) and it is a tool to make sustainable consumption accessible to everyone (30%) (BVA Doxa 2021).

Finally, Italy appears to be one of the most interesting markets for research on second-hand platforms also compared to other major European markets: it is the third EU country for spending on clothing and apparel, after the UK and Germany (Statista 2020a). Similarly, as it will be examined in the next sections of the chapter, both Depop and Vinted have Italy as the first-ranked European country for users (Similarweb 2022), while Zalando is the first fashion marketplace in Italy outperforming any other fashion marketplace in the country (Statista 2021e; Statista 2021f; Statista 2018a).

1.2.2 Second-Hand Fashion Platforms: A Brief Conceptual Evolution

In the last ten years, the Internet and mobile technology have given rise to the so-called sharing economy. In this overall context, second-hand fashion platforms were included in the wider plethora of platforms under the sharing economy model and collaborative consumption umbrella. Sharing economy platforms can be defined as multi-sided platforms (B2C and C2C) that enable ownership and usership of goods, skills and services by bringing together two or more distinct groups of users (Netter and Pedersen 2019). At its core, sharing economy includes a variety of different products and services, such as short-term hospitality and ridesharing apps, as well as fashion reselling and swapping platforms. These sharing platforms can be then considered part of a collaborative consumption model, in which consumers exchange services or goods in exchange of some monetary compensation (Luri Minami, Ramos and Bertoluzzo 2021). In this defined context, second-hand clothing apps can be inserted in both the sharing economy and collaborative consumption phenomena. In fact, they allow their users, both businesses and individuals, to share clothing items (sharing economy) through a selling-buying trading system (collaborative consumption). Overall, this results in easing a quick, convenient and immediate access to second-hand garments to a wider audience. Additionally, in the last five years, second hand fashion platforms have also emerged as an alternative for breaking the fast fashion cycle and extending the clothing lifespan. Therefore, they can be also inserted in the wider fair fashion phenomenon (Netter and Pedersen 2019).

1.2.3 Business Models of Second-Hand Fashion Platforms

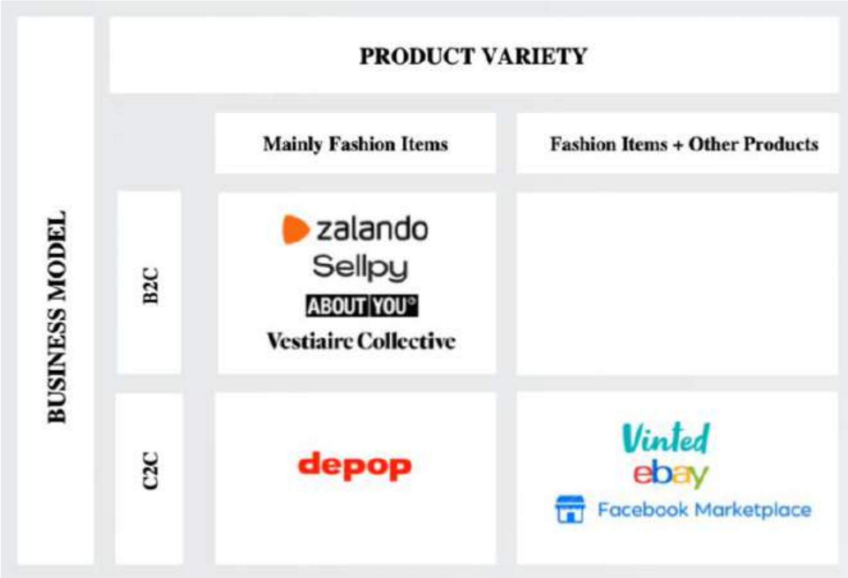
Throughout the world, secondhand fashion platforms have predominantly taken two forms: business to consumer (B2C) and consumer to consumer (C2C). Regardless of the format, a market maker – platform – almost always exists to intermediate transactions and match supply and demand (Hagiu and Wright 2015).

Within the B2C oriented business models, the business is based on a reseller (the platform itself) that buys the products from a supplier (e.g., an end consumer or another business) and sells it to the end-consumer (Hagiu and Wright 2015). In this category, a diverse set of players can be found in Europe. Next to startups, online e-retailers such as Zalando or ABOUT YOU do have their own second-hand marketplaces (e.g. Zalando Second Hand). Similarly, traditional fashion companies like H&M, with its secondhand platform Sellpy, have entered the market (Arnett 2020; Binlot 2019; Goddevrind et al. 2021).

On the other hand, a C2C-model can be defined as a system where the platform or app only works as an intermediary merely facilitating the interaction between sellers and buyers (Hagiu and Wright 2015). In this case, the seller (a brand or a single individual) posts the fashion product on the platform, selling the item directly to other platform users.

Overall, a wider plethora of marketplaces and platforms can be found. It is possible to include in this category platforms like Vinted, Vestiaire Collective and Depop. Similarly, other major players, such Ebay and Facebook, have entered the secondhand market through the launch of C2C marketplaces (Arman and Mark-Herbert 2021). Figure 2 summarizes the major players discussed.

Figure 2: Overview of Main Market Players in Italy



1.2.4 Relevant Second-Hand Fashion Platforms in the Italian Market

Looking at the Italian market directly, Vinted, Depop, Vestiaire Collective, Zalando Second Hand are the major competitors, which has been our rationale to consider them for the further research (Statista 2021g; Statista 2018a). The market research and intelligence company Similarweb confirms the importance of the four mentioned players. Similarweb provides research intelligence and website traffic services throughout various industries.[1] Overall, the Zalando app ranks 8th in the "Shopping" category, and 1st for strictly fashion-related apps.[2] Therefore, it is also assumed that the "Second Hand" category within the Zalando online shop is frequently used. The usage rank algorithm on Similarweb.com, on which the app ranking is based, takes current installs and active users in the last 28 days into account.

As the foundation for the general understanding of the business models and the functionality of the apps, which will be relevant in the context of conjoint and perceptual analysis, the different players will be introduced in the following.

[1] https://www.similarweb.com
[2] Screenshots of the app usage analysis provided by Similarweb.com are attached in Appendix 11.1

C2C

Vinted is a Lithuanian C2C clothing reselling and swapping platform founded in 2008.[3] The company operates in 15 markets including the United States, Portugal and Italy, with approximately 50 million users. The product portfolio of Vinted is relatively wide and doesn't focus on a specific type of fashion. However, it also includes accessories and has, most recently, introduced home décor and household goods.

On the C2C marketplace, buyers and sellers interact directly. The seller is responsible for the presentation of the products and their descriptions. Besides the option to sell and buy items, Vinted also provides the option to swap. Vinted has traditionally been free of charge for both buyer and seller. Yet, in 2014, the company introduced seller fees, which incurred criticism. As a result of this criticism, Vinted made basic usage of the app free for both transaction parties (Li 2015). Today, Vinted generates revenue through ad banners and premium features regarding the selling and buying process. First, it offers sellers the possibility to create more visibility for their products through a fee. Paying this fee, the products of the seller appear to other users more frequently. Second, Vinted has introduced a buyer protection mechanism for a fee consisting of a variable component (5% per purchase), and a fixed component (€0.70 per purchase). This option is presented as a "Buy now" button, where the fee is charged automatically if the buyer clicks it. Through this button, the buyer will be refunded in case the product does not arrive, is damaged, or significantly deviates from its description. However, the buyer can also interact with the seller directly to arrange the purchase without the involvement of Vinted. In general, in case the customer changes their mind after the purchase and wants to return the items, it is their responsibility to negotiate with the seller who is not obliged to accept the return. As for the payment methods, Vinted is offering the payment via credit and debit card,

[3] If not marked differently, the information on Vinted is taken from https://www.vinted.com throughout the section.

Apple Pay and Google Pay. In addition, it provides the option to pay through a Vinted Wallet, which contains the money earned through previous transactions.

Depop is a UK-based re-commerce fashion platform founded in 2011 in London.[4] Initially, the website was a social network for readers of a design and arts magazine, which enabled purchases between readers and the young creatives featured in the magazine. Today, Depop operates in more than 150 countries, with more than 30 million users. The emphasis of the platform is generally on vintage fashion, but also other fashion types and other products such as cosmetics. In 2021, Depop was acquired by Etsy, a marketplace for creative and artistic goods, but still operates independently.

Similarly to Vinted, Depop sellers interact with the customer directly and are also responsible for the product presentation and shipment. But it differs from Vinted because it operates on a commission model, charging a fee of 10% from the purchase price, in addition to a transaction fee to the seller — which represents the main revenue source for the company. Similarly to Vinted, every transaction made through the “Buy Now” button is subject to buyer protection. This guarantees a refund in case the item does not arrive, or its condition is not as described. Moreover, it is possible to negotiate with the seller directly without the involvement of the platform. It is the customer’s responsibility to negotiate a return in case its reason is not covered by the buyer protection mechanism. Depop provides the payment options credit and debit card, Google and Apple Pay. Depop also includes PayPal within its payments ecosystem but does not provide a Depop wallet like Vinted does.

[4] If not marked differently, the information about Depop is taken from https://www.depop.com/ throughout the section.

B2C

Vestiaire Collective is a French luxury and premium secondhand platform founded in 2009 in Paris.[5] As of 2020, the company operated in 90 countries and had 9 million users (Dillet 2020). Operating in the luxury market, counterfeits play a significant role for the company. The authenticity of the products traded is assured through a high level of involvement of the company in the sales process. Vestiaire Collective operates as a hybrid model, acting as a reseller and a marketplace based on a consignment model. We decided to assign the platform to the B2C category because the sales process does not purely take place between customer and customer as the platform is involved to a relatively high degree. Further, Vestiaire also allows professional sellers to trade on the platform.

After the seller has listed their items on the app or the website including description and pictures, Vestiaire Collective employees check the listing before it goes live. It is the seller's responsibility to present the product accurately and answer customer questions. From the sales onwards, the further process can take on two different paths. On the one hand, if wished for, once the product is sold, the seller sends it to the company, which confirms the authenticity and the quality of the product. From a monetization perspective, the buyer is also involved, being charged €15 for a quality and authentication check of the item sold. On the other hand, since recently, it is also possible, that the item is directly sold to the buyer. In any case, in return, the seller receives up to 80% of the selling price after the deduction of a fee. In both cases, when doubts regarding the authenticity of the items arise, Vestiaire Collective offers support through their customer service. As such, there is some sort of buyer protection provided independently from the quality check.

[5] If not marked differently, the information about Vestiaire Collective is taken from https://www.vestiairecollective.com throughout the section.

The return policy of the company depends on the type of seller. Similar to Vinted and Depop, if the seller is an individual, then the buyer has the opportunity to list the item again and sell themselves. Vestiaire Collective charges a fee, depending on a timely delivery for the customer. If the seller is a professional, the customer can return the item to Vestiaire Collective within 14 days after arrival. Vestiaire Collective provides the following payment options: credit card, PayPal, Google and Apple Pay and the option to pay in rates.

Zalando Second Hand, originating from "traditional" online fashion retail, after experimenting with local second-hand initiatives, entered the second-hand market in September 2020.[6] In March 2020, the company announced that it would add a so-called "pre-owned" category to its online shop starting with the German and the Spanish market. Since April 2021, the pre-owned category is also available in Italy under the name "Second Hand". The business model, according to the definition given in chapter 2.3, can be classified as a resale model. Zalando Second Hand selling and purchasing process can be described as follows: the seller finds the option to sell in their personal account on the website or the app. They upload pictures of up to 20 items and in return are offered an automatic credit for each item. This credit can then be used to buy other items on Zalando or donate to a charity. With the opportunity to sell up to 20 items at once, Zalando aims to provide a uniquely convenient and competitive reselling solution.

Within 1-2 days, the company assesses the fulfilment of the acceptance criteria of the items. Zalando only accepts a certain selection of brands and all items must be in a "like-new'' condition. Within the assessment process, the prices initially communicated to the seller can still change and are then again communicated to the seller who can accept or decline. After the customer has sent the items to Zalando, a quality assessment is conducted. The seller receives their credit. As the purchase process is completed at this stage, it can be assumed that Zalando

[6] If not marked differently, the information about Zalando Second Hand is taken from https://corporate.zalando.com/ throughout the section.

is then initiating the product presentation and the upload of the purchased items in the online shop and in the app.

The sales process for the secondhand category works similarly to the one for new items and the online shop. Customers add what they want to their basket on either the website or app, then they can start the payment process. Zalando takes care of the shipment. It is also possible to return secondhand items. Zalando offers payment support for the most common debit and credit cards, PayPal and, as described before, the use of vouchers received through previous sales of secondhand clothes as means of payment.

Besides its B2C reselling model, Zalando also launched Zircle, a separate C2C reselling platform and app. The company aims to remove uncertainty connected to C2C trade by offering a return option for items bought directly from other consumers. However, as this service is currently only available in Germany for female clothing, it will not be discussed further in this thesis.

While this chapter provided the relevant market context, the next chapter will set the foundation from a literature point of view, considering the findings of previous consumer behavior studies in the secondhand clothing industry, with research methods applied further into the thesis.

1.3 Literature Overview

The following chapter aims to discuss to the current literature on clothing resale platforms, shedding light on consumers' perceptions and preferences. Furthermore, as a consequence of the current industry growth and evolution, the goal is also to assess the new and current consumer segments that participate in fashion sharing platforms.

At first, the chapter will provide an overview of the different studies already performed related to the second-hand fashion platforms topic. Secondly, the chapter will describe the various marketing analytics approaches that are going to be adopted and assess which specific attributes and characteristics should be tested in both perceptual maps and conjoint analysis. Finally, we will deepen into the ex-post segmentation approaches and the relevant descriptors that must be considered when assessing second-hand fashion consumers.

1.3.1 Consumer Motivations and Platform Characteristics: an overview

Previous research has looked at the subject from several perspectives. For the aim of this dissertation, we will only focus on the online fashion resale segment. Eight relevant papers were found with key insights on consumer perceptions and platforms characteristics as an overview of the online second-hand fashion industry.

Netter and Pedersen (2019) describe the motivations driving consumers to participate in fashion reselling and swapping platforms as "self-interest related (convenience, recreation, and product portfolio)", affirming that buyers of second-hand clothes are "less likely to hold critical positions. More specifically, they appear to be driven primarily by functional motives, i.e. the convenience of the service and the products on offer, followed by hedonic motives". Other authors such Armstrong and Park (2020) examined online clothing resale platforms topic, investigating the actual consumer behaviour of online clothing resale platforms users. The author conducted 24 qualitative interviews with female young participants using second hand clothing platforms to buy and sell garments. The study resulted in concluding that elements like overall affordability, ease of use, trustworthiness and reliability, security of payments, variety and quality are the main factors considered by the users.

Additionally, other researchers investigated the fashion marketplaces characteristics and consumer preferences. Lee at al. (2021) analysed several fashion sharing platforms operating both outside and inside South Korea, assessing several website characteristics through a Likert scale methodology. The study revealed that the sharing price, a well-categorised and wide products variety, the advertised products hygiene and a more effective platform usability and accessibility were huge factors influencing engagement and purchase on such platforms.

Furthermore, according to another study conducted by Luo et al. (2020), service quality, including features such system quality, security assurance, product variety, and service support, as well as and community quality were identified as determining characteristics of second-hand e-commerce purchase.

Similarly, Parker and Wang (2016) analyse the consumer of second-hand clothing platforms, exploring their engagement and behaviour on fashion retail apps and make suggesting on their design and set-up. 18 qualitative interviews were conducted and the study "identified efficiency and convenience as two of the most important motivators for engagement, with personalized services, and convenient operation process being also dominant functions" to attract customers to shop on fashion apps. Instead, the "social shopping" factor registered divisive results, demotivating users in their purchase. This contrasted with other authors discoveries on the same factor (Luo et al. 2020; Netter and Pedersen 2019).

Other authors such Abbes, Hallem and Taga (2020) analysed collaborative redistribution platforms characteristics and their correlation with loyalty intentions among users. 28 consumers were interviewed, and the study discovered that “ease of use, seller's reputation and trust, community belonging, and entertainment had an overall impact on brand loyalty intentions”.

Other researchers, instead, conducted several analyses on motivations of purchase rather than the platform characteristics (Guiot and Roux 2010, Laitala and Klepp 2018). Overall, researchers successfully identify the motivations driving the purchase as follows: ethic motivations (sustainability and mainstream fashion industry negative perceptions), economic motivations (price and platform convenience) and hedonic factors (fashionability and coolness mainly) as the main drivers of second-hand purchase.

Italy, on the other hand, appears to have poor literature about the topic, consisting primarily of graduate students’ final works on circular economy and motivations of purchase (Occhipint 2021; Tortorella 2021). Therefore, the analysis of Italian consumers will be conducted mainly referencing to the previously mentioned literature. Table 1 summarizes the literature overview previously described.

Table 1: Literature Overview Summary

Author	Content and Findings
Netter and Pedersen (2019)	Investigates online fashion resale platforms users behavior, discovering that US consumers use fashion reselling and swapping platforms for self-interested and functional reasons (convenience, recreation, and product portfolio)
Armstrong and Park (2020)	Investigates women online clothing resale platforms behavior in the US. The study identifies some factors influencing usage: affordability, ease of use, trustworthiness and reliability, payment security, variety, and quality
Lee at al. (2021)	Study conducted on fashion sharing platforms to assess various website characteristics perceptions. Findings revealed that sharing the major factors influencing engagement and purchase were: price, variety, product hygiene, platform usability and accessibility.
Luo et al. (2020)	Study conducted on Chinese consumers using the second-hand platform Xianyu. The results identifies service quality and community quality as determinants of trust and purchase.
Parker and Wang (2016)	Investigating UK consumers' engagement and behavior on fashion retail apps in order to assess the platforms design. Efficiency, convenience, personalized services, convenient operation process were main determinants of purchase. Social shopping, instead, demotivated consumers to purchase.
Abbes, Hallem and Taga (2020)	Qualitative study conducted on French consumers regarding second-hand shopping platforms. Ease of use, seller reputation and trust, community belonging, and entertainment were validated as key factors for brand loyalty intentions.
Guiot and Roux (2010)	Study conducted on French Consumers assessing consumers motivations in purchasing second-hand clothing. The study revealed 3 macro motivations driving the purchase: economic, hedonic, and critical motives.
Laitala and Klepp (2018)	The paper explores the motivations of second-hand clothing acquisition in Norwegian consumers. The main motivations highlighted in the study are: economic (price), environmental concerns, fashionability and trendiness, hygiene and product quality, uniqueness, style and fashionability, social recognition.

1.3.2 Perceptual Maps

One of the techniques that will be implemented in the following work project is perceptual mapping. The method will be used to represent consumer perceptions regarding second-hand platforms.

Perceptual maps have played an essential role as analytical tools in marketing research to determine brand perceptions (Chadha and Kapoor 2008). The map draws out a clear picture to describe consumers' perceptions based on specific attributes and the relationship between those attributes (Chadha and Kapoor 2008). Marketing managers use perceptual mapping techniques to make product positioning decisions, an essential component of competitive marketing strategy (Kohli and Leuthesser 1993). Establishing brand value with strong product positioning leads to survival in the competitive business and facilitates profit generation (Chiang, Lin and Wang 2008; Gigauri 2019). In this context, a perception map "for online brands can provide a practical view of the associations and similarities among online companies or online products for developing branding strategies" (Gigauri 2019).

There are three main factors to consider while structuring positioning strategies: (i) Target customers (ii) Target competitors and (iii) Competitive advantage. Perceptual maps help to reveal the target consumer's perceptions about the company's product and competitor's product at the same time (Najafizadeh, et al. 2012). It allows to evaluate the current market position and develop future positioning strategies to strengthen brand image in consumers' minds (Najafizadeh, et al. 2012). As mentioned earlier, since these maps provide a visual representation of the gaps in consumer needs and preferences, they can help companies to improve their product and services market positioning (Gower et al. 2010). For instance, in a study by Tractinsky and Oded (2003) related to the saturated e-retailers market, the author used perceptual maps to detect the similarities and dissimilarities among the current players of the market and find the ideal combination of attributes in consumers' minds to recommend gaps where the e-retailers can grow.

1.3.3 Consumer's Perceptions: Relevant Factors to Test

In order to assess consumers' perceptions regarding second-hand platforms, it's important to explore what are the relevant aspects to test. Brand management consumer theories will be the primary source of information for considering and structuring brand perceptions (Keller 2001; Aaker 1991) as well as similar studies conducted on e-retailers using perceptual maps (Tractinsky and Oded 2003). We are making this choice due to the following noteworthy aspects: (1) the acknowledgement and the relevance of both rational and emotional aspects in brand evaluations according to these theories; (2) despite providing a detailed framework for brand building, such theories are also applicable to specific uses and can be refined and edited to meet the requirements of their users.

We will refer to the literature overview to match the correct aspects that should be examined referring to second-hand clothing platforms with brand theories. Indeed, we can summarise the most important characteristics to test in perceptual mapping as follows.

<u>Price and Value for Money</u>

For consumers, the brand's pricing and monetary policies might build connections with the the brand price level in the category. Therefore, a business's pricing approach influences how customers classify the brand in terms of its monetary value. Second-hand consumers are then defined as "highly economically-oriented bargain hunters" (Seo and Kim 2019), which makes this a particularly important factor to test in the purchase of resale fashion. According to Armstrong and Park (2020) second hand clothing platforms need to deliver "more competitive price than regular fashion platforms". As well, the author affirms that buyers use second hand platforms for accessing a "a wide variety of goods ordinarily outside one's budget". Similarly, Armstrong and Park (2020) examine how consumers evaluate prices, shipping costs and retail value when assessing the convenience of a platform (e.g. “users of Facebook Marketplace preferred the absence of fees and shipping charges in their pursuit of the best price”). Netter and Pedersen (2019) defines price-sensitivity as a main determinant of purchase in second-hand platforms, both translated in the willingness to save money and as a way to find great brands at affordable prices (e.g. possibility to find “great deals” or “XY brand for great price”).

<u>Items Quality</u>

Customers have a variety of perceptions about brands, but the most significant are those that relate in some way to the brand and its products’ perceived quality. Other important aspects of quality are perceptions of value and satisfaction compared to the price paid. Hur (2020) observed that quality is a driver of consumption of second-hand fashion, with concerns over poor product quality being dominant in his research results. The perceived negative items quality (e.g., unclean and poor-quality material) led consumers to feel less secure about the product and the platform. It is also confirmed by other sources (Laitala and Klepp 2018; Lin et al. 2016). For example, Lin et al. (2016) affirm that “consumers who buy second-hand products seek better quality” and that “quality and durability are characteristics that consumers look for in this type of product”. Armstrong and Park (2020) affirm that “a clear priority of SHFCs is to maintain an inventory of goods that reflect the condition, quality, and trendiness of those offered in the conventional fashion marketplace”. According to Hur (2020), another dominant pattern within the quality concern is the product hygiene (i.e. bad smell, feeling dirty or not fresh). In fact, the research showed that some consumers do not purchase second-hand clothing because they perceive it as “not clean”. Similarly, Laitala and Klepp (2018) affirm that dirtiness and feeling that it is unhygienic might be linked to wearing second hand clothes. Similarly, Machado et al. (2019) and Netter and Pedersen (2019) confirm the quality element as a key determinant.

Platform Reliability

Customers, as previously mentioned, have a broad view of a product or service performance. As a result, characteristics including the speed and accuracy of service delivery, risk minimization (trust), and the promptness and helpfulness of customer service influence views of products and service performance. According to Kim and Ahn (2007), customers purchasing second hand clothes highly rank the degree of trust that they have towards the platform provider, with characteristics such as seller's expertise, platform security and reputation playing a key role in the trust building process. Luo et al. (2020) analysed Xianyu (Taobao second-hand platform) demonstrating that perceived trust increased transaction intention. Netter and Pedersen (2019) define this aspect on second-hand sharing and reselling platforms as "a safe means of acquiring and disposing pre-owned items" linked to elements such as protection of personal data and buyers' protections". Armstrong and Park (2020) examine how second-hand platforms users embodied "considerations of risk and uncertainty derived from questionable trustworthiness and unreliability compared traditional approaches to buying and selling" (…) "Getting scammed" or "screwed over" is an ever-present potential, driven by aspects of both the platform itself as well as other users. For buyers, fraud is an inherent reality to shopping, making the web features, policies, and communication of the platform critical to perceived trustworthiness."

Design and Style

Consumers may have associations to a service that transcend its practical elements and include more aesthetic aspects. As a result, sensory factors such as the product-service design and style appeal may have an impact on performance. Lee et al (2021) examine how the "user's degree of recognizing the location of the information tree, suitability of the website's visual imagery, consistency of each web pages, icons, graphics, text and indexes appeal" were key determinants in the consumers' engagement and purchase for fashion sharing platforms.

Fun and Entertainment

When examining brands, fun becomes another upbeat type of feelings in assessing the brand consideration. Consumers might feel amused, light-hearted, joyous, playful, cheerful towards a specific brand and so on (Keller 2001). Fun and excitement are also part of the Aaker analysis on brand personality (Aaker 1991). According to Abbes, Hallem and Taga (2020), there is a direct correlation between increased brand loyalty and sense of entertainment and fun on resale platforms: "collaborative platform can be perceived as a means of entertainment through the induced enjoyment which is considered as a primary factor explaining the continued use of a platform (…) This entertaining aspect supports the will of the consumer to re-use the platform. The entertaining aspect of the platform has a direct positive influence on platform loyalty intentions". Additionally, second-hand consumption is associated with treasure hunting. Treasure hunting is "a concept related to the pursuit of something that is not available in the market (…). When consumers find collectable items or products that are not available in the market, they experience emotions of pleasure and amusement" (Machado et al. 2019).

Service Quality and Sophistication

According to Aaker (1991), when evaluating a brand, it is important to assess sophistication as a key element to understand how the brand is positioned in consumers' mind. Sophistication is intended the idea of offering of basic/standard service versus a more sophisticated and upper-level service (Aaker 1991). As well, in the case of the purchase of pre-owned items, the level of sophistication of a service seems to be an important aspect to evaluate especially when purchasing vintage and premium-luxury items (Cervellon and Vigreux 2018; Secondulfo 2016; Zaman et al. 2019).

Sense of Community

Another relevant aspect to test in brand equity is the sense of community that consumers nurture towards the brand examined. Similarly, second-hand purchase is also highly associated with a sense of community. The social dimension and the possibility of weaving and nurturing relationships, both with sellers and with those who share the same interests as the consumer (other consumers) are components of the shopping experience and are important determinants of the purchase. For example, according to Luo et al. (2020) the sense of community had a direction consequence on the motivation to purchase. Similarly, Machado et al. (2019) confirm that the relationships with sellers and other second-hand customers is a determinant part of the purchase in second-hand fashion. Finally, Netter and Pedersen (2018) define the "social component" (the "community spirit", "great girls" factor) on resale fashion platforms as a determinant part of the purchase. This is also confirmed by other authors (Parker and Wang 2016; Abbes, Hallem and Taga 2020).

1.3.4 Conjoint Analysis

Another technique that will be implemented in the work project is conjoint analysis. Therefore, it is important to discuss this method, giving some definition and briefly exploring the literature about the topic.

Rao (2014) defines conjoint analysis as a marketing analytics method estimating consumers' preferences related to products or services features and their possible combinations. Rao further explains that the technique measures the combinations of the different product-service feature levels, scoring the different set of choices purposed to the consumer. This method is then also defined as "decompositional" since it decomposes the consumer preferences through the choices made by respondents and then it creates partworth functions, explaining the importance of each attribute level (Green Srinivasan 1978).

Major conjoint analysis methods are: (i) Traditional conjoint analysis (CA), (ii) Choice-based conjoint (CBCA) or choice-conjoint analysis (CBC) and (iii) Adaptive conjoint analysis (ACA) (Rao 2014). For our research purpose, the CBC method will be chosen since it can provide us the most accurate insights about the consumer's preferred attributes on online second-hand platforms. This method allows market researchers to directly translate the consumer's preferences by giving them several combinations of "choice sets" driven from selected attributes and levels, and consumers "choose" the ones they would most likely purchase in the marketplace (Johnson 1974).

Two major steps must be considered when designing a conjoint analysis study: (i) identifying the product attributes and levels (ii) choosing the most suitable approach (choice-based or rating-based analysis) (Rao 2019).When identifying the attributes and their levels, Green, Krieger and Wind (2001) suggest to conduct focus-groups, in-depth interviews with users and take insights from corporate experts, especially before moving to next stage of the research. In the case of the choice-based conjoint, the following steps are then performed: (1) designing the set of choice (2) the data collection phase (3) the data analysis part, leading to partworth functions and attributes trade-offs.

From a literature standpoint, it is possible to state that conjoint analysis enabled many successful marketing studies related to new products launches, existing products implementations and pricing. For example, several conjoint analysis studies were listed in the Bagozzi's book (1994). These studies allowed to implement several conjoint analysis techniques, assessing consumers choice decisions on both FMCG (i.e. deodorants) and fashion items (e.g. jeans and sneakers) (Bagozzi 1994). Other studies retrieved in the book Principles of Marketing Engineering and Analytics by Lilien, Rangaswamy and De Bruyn (2017a) discussed the application of conjoint on-air pollution machinery, hotels and beers products launches. Similarly, Silayoi and Speece (2007) used conjoint analysis to assess consumer preferences in packaging designs and investigate how specific packaging attributes influenced consumers like hood towards a product. Finally, Lu and Zhang (2020) also used the CBC technique to check the consumer's decision about online marketplaces.

1.3.5 Conjoint Analysis: Attributes to Evaluate

To understand the second-hand marketplace economy, it is important to assess how users make a choice among different marketplaces when buying pre-owned clothes. The following section is going to examine the attributes consumers consider when making online transactions on marketplaces (Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016; Lu and Zhang 2020). We will later use these attributes to conduct some qualitative interviews with customers and experts and assess which set of attributes we should include in the conjoint analysis survey. In order to scope the attributes range, we will be examining the literature related to the topic.

Brand Level

The first aspect that we are going to test is the brand level. Indeed, according to Lilien, Rangaswamy and De Bruyn (2017a), using brands as part of the attributes analyzed in conjoint can be a useful way to test how potential product characteristics perform across various brands and competitors in the market. By this way, it is possible to assess the products feature selection and pricing both at a single brand level and competitors' level (across brands). Therefore, marketers are allowed to play a "what-if" scenario where they can verify new business ideas and compare the brand performance with those of competitors.

Price Level

From an economic perspective, the motivations inherent in second-hand shopping rely on price sensitivity and/or price awareness. Fair price motivation can translate into the desire to pay less or to search and obtain good deals for the price paid (quality-price optimisation) (Guiot & Roux, 2010; Ferraro, Sands and Brace-Govan 2016). In the case of second-hand fashion, economic motivations have historically proven to be an essential factor in the second-hand purchase decision (Laitala and Klepp 2018; Guiot and Roux 2010; Seo and Kim 2019). Similarly, Lee et. al (2021) describe sharing fashion e-commerce consumers as particularly driven by convenience and rational consumption. According to this study, fashion sharing platforms clearly showing their fees rates demonstrated higher consumer engagement than those not performing the same transparency. These results demonstrate that consumers who use fashion marketplaces are taking into consideration the fees paid and the overall platform convenience (Lee et al. 2021).

Variety

E-fashion purchases are also influenced by product and brand variety. According to Lee et al. websites offering diverse brands, products and sizes had higher consumer engagement and preferability than those with poor offering and classification (Lee et al. 2021). Similarly, Alanadoly and Salem (2022) demonstrated that high product variety on online fashion marketplaces positively impacts consumers' perceived quality. Additionally, especially when second-hand consumption is driven by fashionability, consumers tend to purchase second-hand fashion due to the product and brand variety (Ferraro, Sands and Brace-Govan 2016).

Delivery Service: Speed and Costs

The literature widely refers to the delivery service quality as an important attribute determining decision making (Bienstock and Royne 2010; Bouzaabia et al. 2013; Mentzer and Flint 1999; Mentzer, Flint and Hult 2001). According to Lu and Zhang (2020), "any product purchased online needs to be delivered to buyers via a logistics system. Therefore, the online marketplace must ensure the quality of the delivery service by providing a self-managed logistics system or by carefully choosing the logistics partners. Indeed, logistics service quality is an important attribute considered by buyers when choosing the marketplace". This is also confirmed by other authors (Mentzer and Flint 1999; Bouzaabia, Bouzaabia and Capatina 2013).

The delivery service is also connected to the marketplace perceived quality (Richey, Daugherty and Roath 2007; Shet, Deshmukh and Prat 2006). In this case, the platform service is made of two dimensions: e-service and logistics service (Lin et al. 2016). The e-service is a set of e-technologies that allow the consumer to access the delivery service itself (i.e., product information search, order placing and monitoring). Whereas the logistics service is the system allowing the consumer to receive the item: it can be a self-managed logistics (i.e., the seller delivers the item autonomously) or a well-set system that implies an automatic third-party involvement (i.e., a carrier service decided by the platform itself) (Semeijn et al. 2005). Similarly, it is also correlated and associated to other attributes such the delivery speed, carrier reputation and delivery cost (Lin et al. 2016).

Ease of Use

Online marketplaces can be analysed also from a technological point of view. Indeed, their usage and adoption follow the same pattern as any tech platform. Therefore, they have a series of attributes that can be analysed using the "Technology Adoption Model" (TAM) (Gefen, Karahanna and Straub 2003; Yahia, Al-Neama and Kerbache 2018; Hansen, Saridakis and Benson 2018). More specifically, the literature agrees in affirming that marketplace adoption is determined by ease of use and usability as any other e-platform (Hoffman, Novak and Peralta 1999; Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016; Hansen, Saridakis and Benson 2018). Indeed, the literature offers a variegated and diversified list of attributes related to platform adoption. In this regard, we can define usefulness as the utility trade-off provided by the information and digital technologies on online marketplaces (Hansen, Saridakis and Benson 2018), whereas ease of use can be defined as the cognitive effort required to learn and access digital technologies on online marketplaces (Yahia, Al-Neama and Kerbache 2018).

In the specific case of sharing fashion marketplaces, it is important to have "aesthetically pleasing visual information, make product information easy and fast to get, and provide an ease access to items purchase" (Lee et al. 2021). Therefore, ease of use is specifically translated into such characteristics. Indeed, Lee et al. (2021) demonstrated that "websites showing the best usability in terms of language, page consistency, and directory information showed better satisfaction and engagement".

Trust Mechanisms: Payment Guarantees and Transaction Ecosystem

Online resale platforms are marketplaces mainly based on trust (Chong et al. 2018; Fang et al. 2014; Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016). In fact, customers need trust to overcome the fear of buying items from unknown sellers.

Online transactions are also associated with greater financial and legal risk than physical transactions by consumers (Kim and Koo 2016). Consequently, major barriers such as risk and uncertainty prevent users from engaging in online transactions through online marketplaces (Kim and Koo 2016). In order to overcome such barriers, marketplaces act as the intermediary between buyers and sellers, trying to decrease the risk and foster trust (Chong et al. 2018). The instruments providing higher guarantee and protection on marketplaces are defined as "trust mechanisms". Over the years, such mechanisms have been widely applied, demonstrating to be effective in improving the overall transaction environment and the perceived security, decreasing the financial risk (Chong et al. 2018; Bulut and Karabulut 2018; Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016). The institutional mechanisms examined by the literature that we will be taking into consideration are a generally favourable transaction ecosystem as well as dispute resolution systems (Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016; Lu and Zhang 2020).

We can define the transaction ecosystem as the degree of security and smoothness the online marketplace can guarantee the customer when completing transactions on the platform (Bulut and Karabulut 2018; Lu and Zhang 2020). We can define online dispute resolution services and payment guarantees as those systems able to provide buyers and sellers with a solution to issues and complaints arising from the transaction itself. Online Dispute resolution systems and guarantees are also considered to be "the most efficient, cost-effective, and flexible way to address complaints against sellers and protect the buyers’ interests after the transaction has been made” (Lu and Zang 2020).

1.3.6 Segmentation

As any other firm, second-hand fashion platforms compete to meet customers' needs. In order to match these consumers’ expectations, they segment the market and target specific consumers segments. As stated in Chapter 1, the second-hand industry has grown steadily over the last five years. As a result, second-hand reached a broader and more diverse consumer audience. Despite some existing studies on consumer profiles (Markova and Grajeda 2018; BCG 2020) for second-hand fashion consumers, the topic represents an intriguing prospect both academically and business wise, particularly when it comes to assessing and scoping the study to single country consumers where such studies were not specifically aimed for (in our case, Italy). Additionally, Italy represents a good country to assess consumer segment due to the wide-spread second-hand platforms adoption and market growth. Therefore, the following paragraphs provide an initial topic and methodology scoping about segmentation in order to subsequently implement it.

According to Murray et al. (2017), segmentation can be defined as a marketing method used for “differentiating customers based on their individual preferences and desires”. Instead, according to Lilien, Rangaswamy and De Bruyn (2017b), segmentation can be defined as that business and analytical process allowing marketers and firms to divide consumers into groups (segments), evaluating the attractiveness of each consumer group.

Despite segmentation aims to achieve heterogeneity among customers’ groups, clusters might exhibit some responses overlap and segmentation analyses might struggle to produce distinct segments. Therefore, to be useful, an ex-post segmentation should produce a number of segments that has a significant size, assessing the correct cluster number though specific methodologies (e.g. the elbow method) (Lilien, Rangaswamy and De Bruyn 2017b).

Of the many possible ways to segment markets, the following study will take into consideration ex-post segmentation methods that incorporate customers' needs and behaviours. We excluded a priori segmentation since the market research about customers groups was not correctly fitting the current study (BCG 2020). Previous academic or business studies will just be used to consider the descriptors to include in the study (BCG 2020; Markova and Grajeda 2018).

When using ex-post segmentation techniques, marketing analysts generally identify a series of descriptive variables (sex, age, location, frequency, needs etc). By using specific algorithms and correlated softwares, analysts then compute the distances between members based on the attribute responses, creating the formal clusters (segments). According to Murray et al. 2017, to be processed, "attributes are often converted into numerical variables. Instead, in the case of feature-based distance, variables are built using metrics such as median, kurtosis, sum, or purchase frequency, all retrieved from historical data (...)These are then weighted, summed and normalized to create the variables from which distance is calculated".

To perform the current research segmentation, a cluster analysis was implemented, using a specific method: the k-means (centroid-based) technique. This one lies into the partitioning methods category. In this case, analysts divide the data into a predetermined number of groups before reallocating or swapping data to improve some statistical measure of fit (i.e., the ratio of within-group to between-group variation) (Lilien, Rangaswamy and De Bruyn 2017b). In the specific case of k-means clustering, the data are clustering into different groups based on the characteristics and similarity of the data observed. The data analysts decide how many clusters need to be created for the clustering process to work. When a database contains multiple N observations, the partitioning method divides the data into user-specified K partitions, each of which represents a cluster/specific segment. In the case of the k-means technique, the algorithm takes the input parameter K and divides the dataset N observation into K number of clusters. These clusters will contain the N observations that have a high similarity within the cluster (intracluster) but low similarity between data objects outside the cluster (extracluster). The cluster's similarity is determined using a square error algorithm that uses the clusters mean value to divide the data into segments (Lilien, Rangaswamy and De Bruyn 2017b; Damghani, Abdi and Abolmakarem 2018).

This technique was chosen since it was previously and effectively used in several business cases applied to the fashion industry segmentation. For example, Dachyar, Esperanca and Nurcahyo (2019) used k-means clustering for segmenting users of three Indonesian fashion e-commerce platforms. The results showed 5 different customer groups based on their CLV ratings. The segments were named as best, valuable, potentially valuable, average, and potentially invaluable customers. Thanks to this analysis, it was possible to structure a new strategy focused on maintaining customer convenience and increasing customer trust.

Another interesting study is the one by Brito et al. (2015). In this case, k-means clustering was deployed for segmenting online fashion e-commerce customers and assess customer preferences on the fashion platform. The study helped the company to redefine their communication strategy and match the products sold to the customer's preferences.

Ogle et al (2014) used k-means clustering to identify relevant consumer clusters among teenage girls purchasing apparel in the United States. In this research, they analysed the importance that teens assign to various product characteristics they evaluate in fashion products. At the end of the study, researchers identified three clusters namely called the Conventionalists, the Self-Satisfiers and the Embracers. These were defined according to their fashion involvement, social cause involvement, materialism and social responsibility purchasing behaviour. Similarly, Dachyar, Esperanca and Nurcahyo (2019) studied a fashion company in Indonesia, exploring possible market segment for the firm marketing strategy. The segmentation applied k-means algorithm to cluster consumers grouping them into five clusters. Another study (Ganhewa et al. 2021) analysed how to increase sales and demand though a better segmentation and targeting of the fashion retail market. The study was built using, among other techniques, K-means clustering, predicting the sales forecasts for products, customer segmentation consumer demand.

1.3.7 Consumer Profiles: Who are the Second-Hand Fashion Consumers

In order to perform the ex-post segmentation of online fashion reselling platforms, it is important to assess what are the most relevant demographic and behavioural factors to test. These descriptors will be then verified using a qualitative approach (interviews with customers and experts) in order to validate and use them for the quantitative surveys in Chapters 5 and 6.

In the following section, we are going to analyse the literature about the topic.

In terms of age, online second-hand items resale is mainly traded by younger generations: 59% of Gen Z and 57% of Millennials affirms to buy on second-hand items versus 38% of Baby Boomers. Gen Z and Millennials are also the generations buying the most on second-hand online marketplaces (26% and 23% respectively versus 8% of Baby Boomers) (First Insight 2020). Statista research underpins Gen Z and Millennials as most users on resale fashion platforms and as major second-hand fashion purchasers both in 2020 and 2021 in Europe (Statista 2020a, Statista 2020b) and outside the EU (Statista 2021a, Statista 2021c).

Similarly, females seem to be the gender driving the purchase of second-hand fashion with higher participation of women to fashion purchases than men (Markova and Grajeda 2018).

According to Markova and Grajeda (2018), we can also state that most second-hand consumers are in middle- and low-income categories. No information about the relevance of the educational level was retrieved (see experts' interviews in Chapter 4.2 to justify the add-on). Consumers are also categorised in terms of frequency of purchase. Indeed, Boston Consulting

Group (2020) analysed the behaviour of both sellers and buyers, assessing the frequency of purchase as another determinant element to evaluate consumer behaviour of second-hand purchase, although the study doesn't precisely define the frequency cohorts. Similarly, we can categorize second-hand consumers in clusters driven by motivations. Hur (2020) divides consumers into four groups according to the motivations driving the consumption:

- Price-conscious: consumers belonging to this cluster stand out for their high price-sensitivity and as being highly convenience-driven. Nonetheless, these individuals pay particular attention to the quality of the product, favouring the pre-loved segment over the new circuit for the possibility of purchasing goods with high quality/price ratio.
- Style-conscious: consumers interested in the style and aesthetic appearance of fashion items. The purchase and consumption of pre-loved clothing allow individuals to buy second hand clothing for finding unique and cool items and feeling cool.
- Brand-conscious: those looking into the pre-loved segment to buy premium or luxury products. They are looking into second-hand to get a designer item at a lower price, for the enjoyment and satisfaction in searching for branded items and for finding items that can show their status.
- Environmentally and ethically conscious: individuals adopting a conscious and responsible consumption model, paying particular attention to social and environmental purchases. They investigate the second-hand fashion market as an ethical and sustainable alternative to fast fashion and over-consumption.

1.4 Pre-recruitment Questionnaire and Preliminary Interviews

After setting a detailed foundation of our work by describing consumer motivations from different geographical perspectives, delineating the two analyses to undertake - Perceptual Maps

and Conjoint Analysis – with their respective factors and attributes to test, and a final focus on Segmentation which helped us understand the profiles of secondhand fashion consumers, the following chapter will explore the first step of our methodological analysis which revolves around the conduction of qualitative interviews.
Initially, we will describe the interviews' structures and the pillars categories around which questions are elaborated. This step will be applied to both interviews' scripts created, which can be differentiated by the type of respondent: experts and consumers. Consequently, the next sub-chapter will concentrate on analyzing the qualitative feedback obtained through the interviewees, which will provide concrete insights on both external factors, like the secondhand fashion markets, and internal like the user experience on the platforms chosen to study and preferences.

1.4.1 Methodology

According to literature overview investigation and the research objectives, we decided to conduct a series of qualitative interviews with consumers and experts. Indeed, as discovered in the previous Chapters, consumer segments can be potentially described through their age, gender, income status, level of education, frequency of purchase and motivations of purchase. Additionally, they might evaluate different fashion platforms according to their (i) price convenience, (ii) items quality, (iii) platform quality and sophistication, (iv) platform reliability, (v) design and style, (vi) fun and entertainment, and (vii) sense of community. Finally, according to the previous research, elements to potentially test in a conjoint analysis in a similar context are the following: (i) brand level (ii) pricing (iii) variety (iv) delivery service (v) trust mechanism.

However, the literature merely represents a summary of previous discoveries, applied to different nationalities and using different marketing approaches. Therefore, investigating consumer personas and determinant factors to test using qualitative interviews becomes mandatory. Indeed, through the following analysis, we were able to verify the literature overview discoveries and reject those elements that were not pertinent with the research.

This phase was performed between February 24th and March 6th, 2022. At first, we interviewed experts following a semi-structured script. The calls had an average duration of 20-30 minutes and were performed between February 24th and February 28th. The experts' script (Appendix 11.2.1, Table 17) focused on the following aspects: (i) professional experience, (ii) relevant descriptors (iii) motivations (iv) attributes (v) preferences (vi) market perceptions (vii) additional value and future prospective.

The Professional Experience part was aimed to get more details on their expertise in the field, while Descriptors and Motivations questions were used to assess consumers segments characteristics. Instead, the Attributes and Preferences questions were aimed to understand what platform characteristics consumers evaluate the most while using such apps. In the Market Perceptions part, the objective was to get an overview of how experts think consumers perceive the different players in the market and what aspects they might evaluate when comparing one platform to another. Finally, Additional Value/Future Prospective questions were used to assess the impact of the study business and academically wise. We interviewed 7 experts in total.

After having performed experts' interviews, we launched a pre-recruitment questionnaire just for consumers. This was aimed to recruit potential buyers to interview. The pre-recruitment questionnaire included the following sections: (i) residency in Italy (participants needed to be resident in Italy for at least 5 years) (ii) having bought secondhand clothing in the last year (iii) having used at least two of the platforms under examination (iv) age, gender and education (v) frequency of purchase (vi) full name and email. After having reached a sufficient number of contacts we scheduled and performed the qualitative interviews (February 28th – March 6th).

The interview format was a semi-structured one. The authors conducted 11 qualitative interviews with customers following different arrangements (phone calls and video calls). The duration corresponded to an average of 20-30 minutes.

The consumers script (Appendix 11.2.1, Table 18) had five sections: (i) demographics, (ii) usage experience, (iii) motivations, (iv) attributes, (v) preferences (vi) market perceptions. For the first one, Demographics, the objective was to classify the interviewees by their age, gender, frequency of purchase and education. In the second, Usage Experience, the aim was to understand the knowledge and usage consumers acquired with secondhand fashion apps. As for the third, Motivations, the intention was to assess the reasons why consumers used secondhand fashion platforms and why they used certain ones rather than others. Instead, the Attributes category aimed to grasp which were the most relevant attributes interviewees evaluated while using secondhand apps. Lastly, the Preferences and Perceptions section focused on understanding interviewees' perceptions about each app, the way they assessed them and their positioning in their minds.

The channels we used to come across the respondents of our interviews were LinkedIn and Facebook secondhand communities. We opted for these platforms as the size of the network and range of people that we could have encountered favoured the chances to select a diverse sample of people.

In the next chapter, an exhaustive analysis of the results obtained through the different interviews, of both experts and consumers, is going to be described.

1.4.2 Results

The pre-recruitment phase and interviews were conducted between February 24th and March 6th. A total of 18 people, combining both experts and consumers respondents, were interviewed. The main takeaways are presented as follows.

<u>Expert Interviews</u>

We interviewed 6 experts. Their professional experience ranged from 2 years to 15 years. The professionals selected were employed in companies Market Research teams (3), Marketing Management departments (2) and Strategic departments (1).

Three of the respondents confirmed the relevance of age, gender, income, educational level and frequency of purchase to assess the different consumer segments. Two experts suggested additional descriptors: distinguishing between buyers and sellers, assessing if respondents had children or not and including the educational level. However, the seller/buyer descriptor was rejected since the study focuses just on buyers. Whereas the children's descriptor was rejected due to the lack of consistency in the feedback received (another expert suggested to reject it). As a result of the experts' opinions received, we decided to include the educational level in the descriptor part.

Moving onto the motivations driving consumers' purchase of secondhand clothing, experts mentioned the following: Price Convenience (6), Sustainability (6), looking for Unique/Cool items (2), Quality/Price Ratio (2), Bargain Joy (1).

In the case of attributes, the focal point was to identify the attributes users considered while using such platforms. The factors mentioned by professionals will be listed according to the frequency they were cited in the interviews: Trust/Reliability (5), Quality Check and Guarantee

(4), Variety (3), Usability (3), Pricing (3), Delivery Service (2), Visual Presentation of the Items (2), Effortless Shopping Experience (2).

This process helped in finding new factors – which were not initially considered - that could impact consumers in their journey on secondhand platforms. The findings relate to the following qualities: Reputation, Quality check and Guarantees, Price convenience and Service pricing, Presentation of items. It was possible to verify Variety and Delivery as attributes.

The following section will be dedicated to give some qualitative insights coming from the one-to-one interviews.

Regarding the market perceptions' part, the focus was to grasp how the experts think consumers perceive the apps subjects of study in this research (Depop, Vestiaire Collective, Vinted, and Zalando Second Hand). According to experts, Vinted is associated with higher price convenience and less intermediation (buyers can contact other users directly). However, the lack of intermediation also brings a higher risk of fraud and less trust associated with Vinted. Other advantages are the high degree of variety, choice and low commission costs. Depop is considered a minor player, with lower brand recognition and platform usage even in major markets like the UK and Italy. As the sellers' user base is mainly made by professional sellers and vintage stores, it is perceived as more trustworthy than Vinted. The fees and average items costs are higher than Vinted with a higher degree of intermediation. The content produced on the platform is looked upon as more entertaining and visually pleasant (the platform is designed like a social media). Vestiaire Collective is considered to be a niche platform for collectionists and luxury and designer clothing hunters. Its overall pricing is more expensive compared to the previous platforms described. It is perceived as being more trustworthy and secure. Zalando secondhand mainly attracts core Zalando customers who are concerned with sustainability. The main appreciated features of the platform are its pleasant platform aesthetic and navigability, favorable return policies and delivery services, and the items quality. Pricing might be higher than the other platforms, but overall, higher reliability and trustworthiness are associated.

In the last section, the experts confirmed the relevance and additional value of the study especially for the single business players interested in improving their performance or assessing potential product and market gaps.

<u>Consumer Interviews</u>

The interviewees age ranged from 20 to 59, and a robust female representation prevails, covering 9 out of 12 respondents. In terms of frequency of use, there is a higher depiction of people purchasing less than three items in the last 3 months (6). Just two people purchased between 4 and 6 (1) and more than 7 items (1). Regarding their education level, there is a higher representation of people having a bachelor's degree (6), the remaining ones have postgraduate education (3) or a high school diploma (2).

Going over the user experience, 13 apps were mentioned by the respondents: Depop, Vestiaire Collective, Vinted, Grailed, Zalando, eBay, Subito, Shpock, FreedUP, Asos Marketplace, Facebook Marketplace, Rebelle, and Wallapop. The most used is Vinted, known and used by each of the interviewees, Depop, recognized by nine and utilized by three out of the twelve individuals, Vestiaire Collective, acknowledged by eight and adopted by two out of twelve subjects, and finally Zalando with five and three respondents respectively acknowledgments and users out of twelve. Considering the three most mentioned apps above – as they are the most popular – it is possible to state that Vinted still holds onto its favored position when it comes to being used for both selling and buying. As for the other two, there is no clear pattern to follow on any of the two tasks, so it is easy to conclude that clients might feel indifferent. Respondents have been using the mentioned secondhand apps for 1 to 7 years.

Regarding the motivations of secondhand fashion purchase, respondents mentioned the following ones: Sustainability (6), Price Convenience (all respondents), Price/Quality ratio (ed: possibility to buy a good quality item at a comparable lower price)[7] (4), Items Uniqueness and Coolness (6), wider variety than in a thrift store (2).

Moving on to the attributes**,** consumers noticed and prioritized the following aspects: Delivery (3), Payment Ecosystem (3), Price Convenience (2), Items Quality (2), Variety (2), Trustworthiness and Easy Dispute Resolution (3), Usability/Ease of Use (1). This thesis helps in verifying just 6 out of 8. An extra characteristic was mentioned (Items Quality) and had to be added to the list. This helped in highlighting a specific factor which was not previously taken into consideration. Furthermore, they suggested adding additional features to improve the app performance: a quicker and faster delivery service, the insertion of an integrated payment system (e.g., PayPal) or a credit system ("in-app wallet") and a guarantee (against product quality and purchase scams). Further requests relate to the increase of product variety and an overall reduction of prices and purchase fees (referring to Depop and Vestiaire Collective mainly).

Lastly, in the preferences and perceptions section, consumers were asked to identify significant differences between the platforms, giving them a black space to evaluate differences and similarities among the platforms (Table 2). Starting with Vinted, the platform is perceived to have a good degree of item variety, great price convenience (cheapest platform among those examined) providing an efficient delivery service and a medium reliability (less than Zalando, better than Depop). For Depop, the qualities appreciated by consumers and associated with the brand deal with the degree of variety, great engagement, and sense of community. There is a higher attention to item selection compared to the previous platform, which seems to increase the perceived quality with a more efficient reviews system than Vinted. However, Depop results are

[7] Possibility to buy a good quality item at a comparable lower price

more expensive than Vinted and Zalando Second Hand. Consumers' perceptions on Zalando and Vestiaire Collective were more challenging to register as they are less used compared to the previous apps. For Zalando, its aesthetic appearance, navigability, items quality and reliability are characteristics highly appreciated. For Vestiaire Collective, it is normally associated with higher quality and a premium price range (the most expensive platform in terms of both item pricing and fees).

Table 2: Platforms comparison summarized in a table

	Vinted	**Depop**	**Zalando Second Hand**	**Vestiaire Collective**
Variety	X	X		
Usability		X	X	
Delivery	X			
Dispute resolution	X			
Payment ecosystem	X	X		
Price convenience	X			
Review		X		
Quality		X	X	
Countries available		X		X
Item selection		X		

After describing this detailed overview of the qualitative interviews results that we have conducted, it is possible to move on to the next part, which is a more technical investigation of consumer perceptions. In this next chapter, we will explain how we have elaborated a quantitative survey through which we were able to acquire evaluations of the online secondhand platforms, the subject of the thesis, against the seven attributes defined in the literature review. The section will start with an outline of the sample, mainly focused on demographic factors. Then we will dive into the quantitative results obtained to get an in-depth understanding of the associations that consumers make on the platforms.

1.5 Perceptual Maps

Having already verified different aspects discussed in the literature review and conducted preliminary interviews with both experts and consumers, it was possible to retain characteristics and aspects that are significant to understand the different perceptions and needs of the consumers when using these applications. By building perceptual maps it will be feasible to see graphically how the leading secondhand applications are positioned in the Italian market, identify their different strategies and simultaneously it will be possible to recognize if there are any niches in the market.

Firstly, the sample collected, the survey and its method of collection will be discussed. Followed an in-depth analysis of the results obtained from the respondents' demographic characteristics, together with the motivators that drive individuals to use these platforms. Lastly, we will introduce different multidimensional perceptual maps where it would be able to visually display perception of the consumer on both attributes and second-hand fashion applications.

1.5.1 Methodology

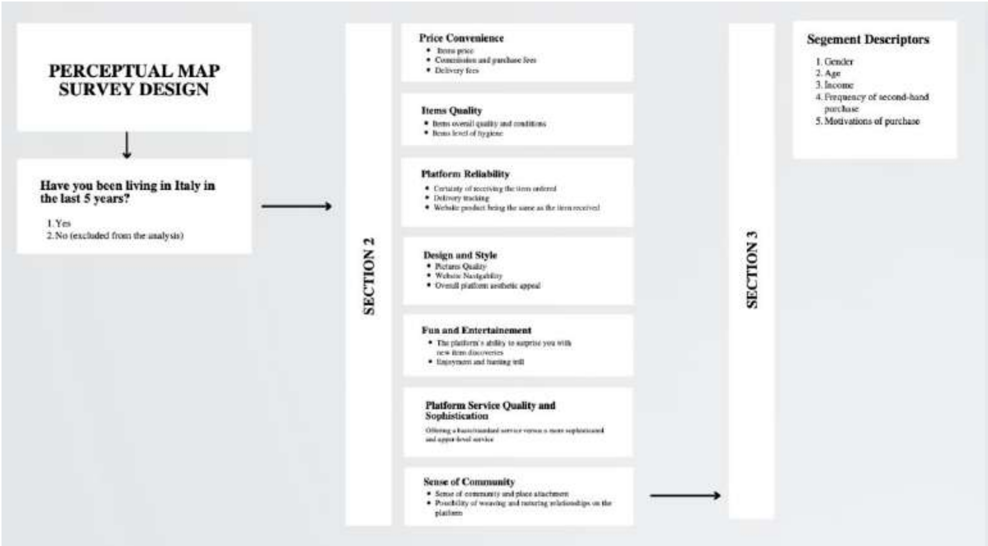
In the interest of analyzing consumers perceptions about the different players under examination (Depop, Vinted, Vestiaire Collective and Zalando Second-Hand), a survey was designed using Microsoft Forms. The questionnaire was first generated in English (Appendix, 11.3.1, Table 19) and then translated to Italian by the native speakers in the team (Appendix 11.3.1, Table 20). The study was carried out among the Italian population and tested only in the native language. This was aimed to increase the respondents' survey comprehension.

The survey consisted of a total of 14 questions. The first question was aimed at assessing whether respondents had been living in Italy in the last 5 years. Responding negatively to the previous question determined the exclusion from the survey. This section was used to check if respondents were Italians and if they were actual second-hand fashion consumers with a certain degree of knowledge of the platforms examined. The second section contained the core perceptual questions. The 7 questions were structured using a 5-points Likert scale. The Likert aimed to assess the buyers' perceptions about each application under examination (Vinted, Zalando Marketplace, Depop and Vestiaire Collective). Participants had to choose a number based on the scale determined at the bottom of each question. The Likert was personalized according to the characteristic examined. For example, Service Quality and Sophistication had 1 corresponding to Basic and 5 equals to More Sophisticated. The same was done with the other characteristics (see Appendix 11.3.1, Table 19 for further details). The characteristics examined were the following ones: (i) platform price convenience, (ii) items quality, (iii) platform reliability, (iv) app design and style, (v) fun and entertainment, (vi) service quality and sophistication, (vii) sense of community. In order to access the third part of the survey, consumers were asked to give feedback to all the sections and platforms under examination.

The last part of the questionnaire contained the sellers' descriptors: (i) gender, (ii) age (iii) monthly income level (iv) how many second-hand clothes they purchased online in the last 3 months (v) motivations driving them to buy second-hand fashion. While the first four questions were a multiple choice, the last one (motivations) contained a 5-points Likert scale where each motivation was supposed to be rated. The motivations examined were: (a) price (b) quality/price ratio (c) buying unique and cool items (d) buying luxury and designers brands (e) sustainability.

The questionnaire had the following overall set up (Figure 3). For further details about the survey design and translations, please see Table 19-20, Appendix 11.3.1.

Figure 3: Perceptual Map Survey Design (overview)



To control any kind of sampling error, it was asked to the professor to review and ensure the clarity of reading.

The survey was launched on different channels, considering the easier access to get a voluntary response sampling (Murairwa 2015) from the market in question. The platforms were the following ones: LinkedIn, Facebook, Instagram, and WhatsApp. The questionnaire was both launched on personal social media accounts (Instagram, Facebook, LinkedIn) as well as on family and friends' groups (WhatsApp). Similarly, the survey was also posted on second-hand clothing and academic research groups, as well as platform-dedicated groups (Vestiaire Collective Italia, Vinted Italia, Depop Italia, Zalando Italia).

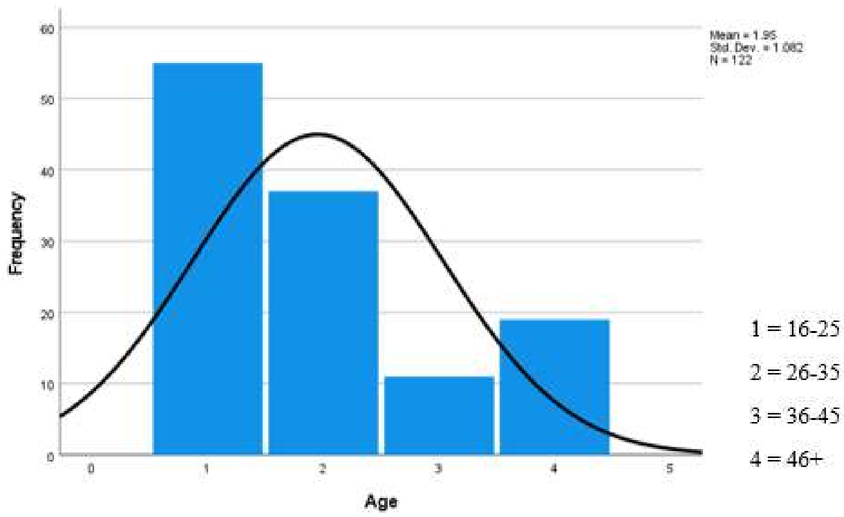
The survey was anonymous, and participants had 4 days to complete it (March 25th – March 28th), resulting in N=130 observations, with an average time to completion of 5 minutes and 15 seconds. 8 respondents were excluded since they were not resident in Italy. Only 122 survey respondents were included in the study whose answers will be taken into consideration to analyze the results which will lead to the creation of the perceptual maps.

1.5.2 Results

Sample Characteristics

Out of the total, just 122 survey responses were considered for assessing the study. According to the survey design, the respondents' age was divided into four different age groups: 16-25; 26-35; 36-45, and 46+. As seen in Figure 4, the age distribution is skewed towards the first age group (16-25), accounting for 45% of respondents.

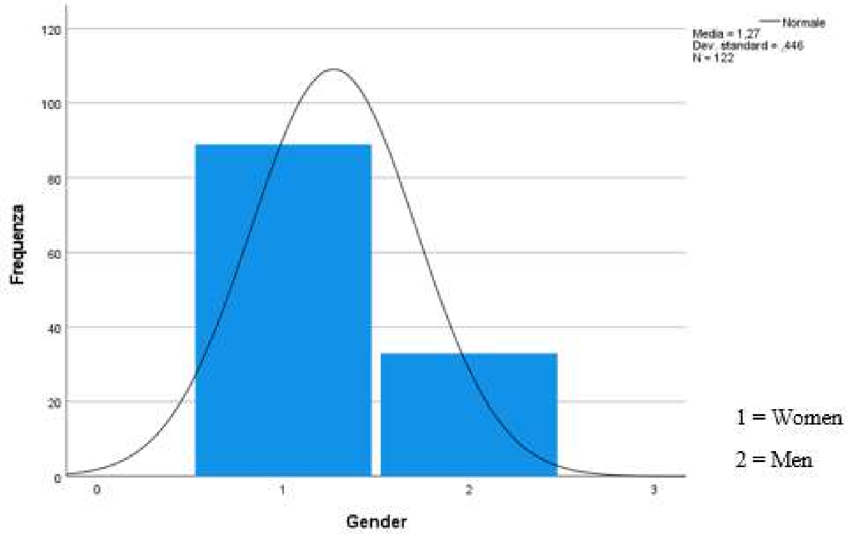
Figure 4: Frequency Distribution Age Histogram



Moving into the 26-35 age group, they account for 30% of the observations. Finally, the third age group (36-45) registers only 9% of the responses, whereas the fourth group (46+) makes up 16% of the observations. These results confirm what was discussed in Chapter 2.4. In fact, it can be argued that users of younger ages (Gen Z and Millennials) are greater resale fashion platforms users than older individuals (Baby Boomers).

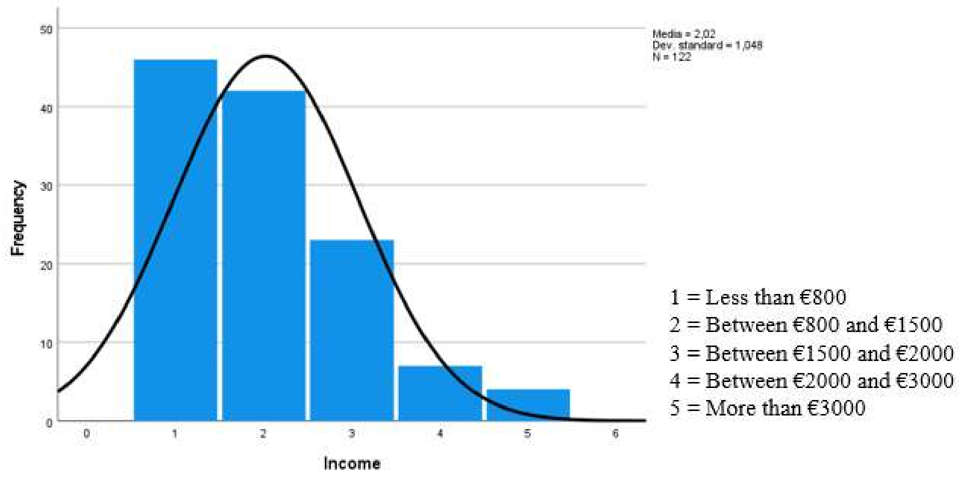
Further analysis of the survey results shows that majority of respondents were women (Figure 5). In fact, of the 122 responses taken into consideration, 89 (73%) were women, and the remaining (27%) were men. Consequently, this creates a significant discrepancy in the study, creating a limitation in the analysis of the results. In order to verify whether women are more likely to use this platform, it would be useful to analyse a larger sample of the population.

Figure 5: Frequency Distribution Gender Histogram



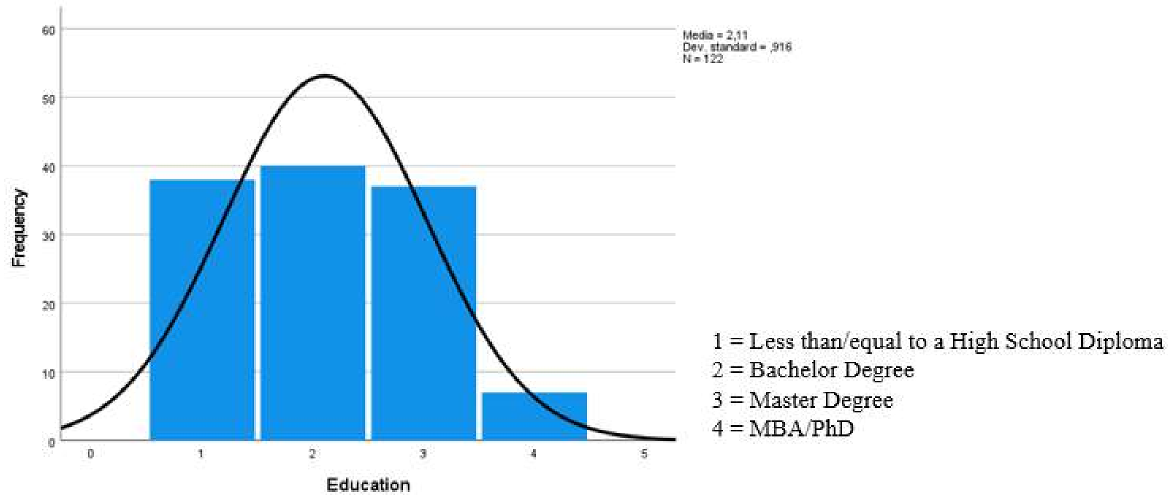
Taking into consideration the income section, it is possible to analyse the sample as follows. As shown in Figure 6, salary was grouped and classified based on the five different income classes (Bird and Newport 2017). 46 individuals (38%) declared to earn less than €800, 42 (34%) claimed to have a monthly income ranging between €800 and €1,500, and 23 individuals (19%) had an income between €1,500 and €2,000. Only 7 individuals (6%) were earning between €2,000 and €3,000 monthly and just 4 respondents more than €3,000 per month.

Figure 6: Frequency Distribution Income Histogram



Following up with the analysis of the education level within the respondents of the survey, it was possible to identify that, out of the 122 responses, 38 individuals (31%) claimed to have less than or equal to a high school diploma as their highest level of education. On to the next scale on the education hierarchy, 40 individuals (33%) of the sample had a bachelor's degree as their highest level of education, and 37 (30%) had a master's degree (Figure 7). Lastly, 7 individuals (6%) declared to have an MBA or a PhD.

Figure 7: Frequency Distribution Education Histogram

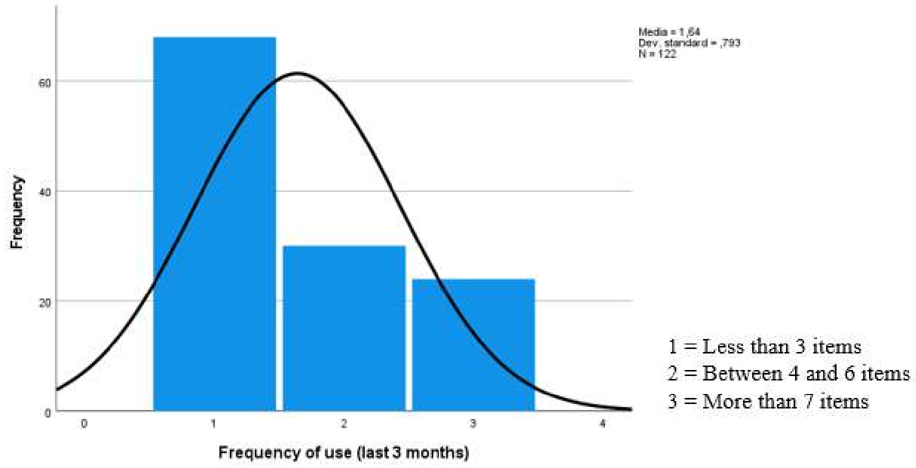


Next, reflecting on the purchase motivations question, this subject was asked with a different Likert scale response options than the previous questions in the survey. In this section, the user can select his motivation to use these apps from 1 to 5, being 1 little influential and 5 very influential. Consequently, to further evaluate it, the responses for the question in matter were divided into each of the motivations, that drive the users to purchase second-hand fashion online. Five different frequencies tables were created to evaluate the percentages of each score and subsequently, analyse which of the motivations would have the most impact on the choice to buy by these means.

The motivation that is recognized to have the most significant impact on the buying decision is sustainability, where 51% of the 122 respondents chose this attribute as very influential when considering buying second-hand clothes online. Two other very important motivations for our sample were: Finding Unique Items, which attributes for 37.7%, and the Price/Quality ratio accounting for 35.2% of the individuals who answered the survey. The remaining two motivations, Lower Prices, Buying Designer and Luxury Brands, do not seem to significantly impact a second-hand fashion purchase through online channels. Hence, results from both the motivations previously mentioned, received the same number of respondants which considered it essential (Likert scale = 5), accounting for 24.6% of the individuals.

Another important descriptor was the frequency of purchase (Figure 8). More than half of respondents revealed to buy less than three items in the last 3 months (56% of the sample). Whereas, the remaining 25% individuals bought from 4 to 6 items and 20% more than 7 items in a three-monthly basis.

Figure 8: Frequency of purchase Distribution Histogram



<u>Multidimensional Perceptual Maps</u>

In order to generate a concrete analysis from the qualitative, a perceptual map was constructed using the statistical software SPSS. The attributes dimensions were then reduced by linearly combining the original variables and the solution of each principal component (Arkkelin 2014).

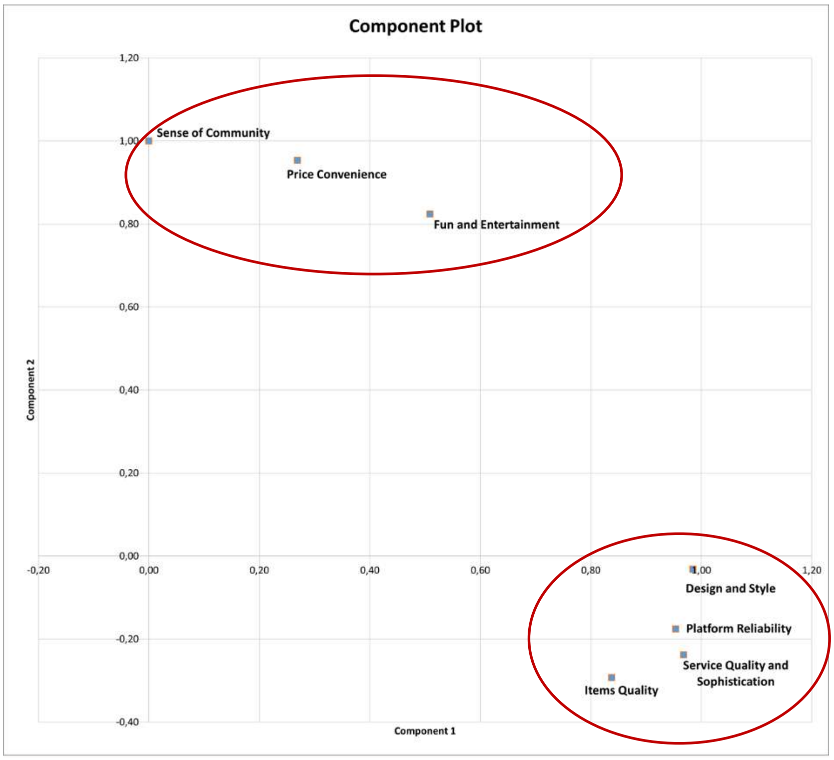
Table 3: Variance and cumulative variances explained by each dimension

Total Variance Explained			
Component	Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	3.851	55.010	55.010
2	2.761	39.442	94.452
Extraction Method: Principal Component Analysis.			

Table 3 above was generated for the means of illustrating the variance and cumulative variances explained by each dimension. For this study, two dimensions will be taken into consideration. The reasoning behind the selection of the number of dimensions goes along with the method being used. Indeed, a dimension is considered significant only if its set of scalars associated with the linear system of equation (eigenvalues) are higher than 1 (Cliff 1988).

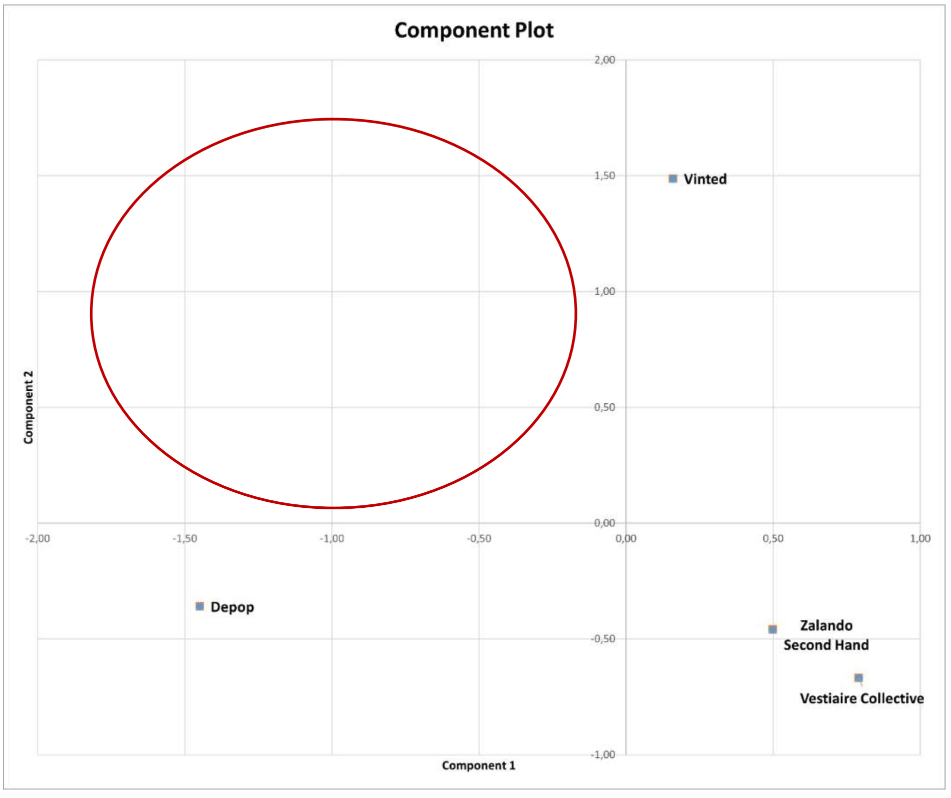
Therefore, it can be demonstrated that the cumulative variance of this study is justified byt the two dimensions model selected, accounting for 94.52%. Just leaving a small percentage (5.48%) remained unexplained, meaning that the model was not justified byt the factors selected (Table 3). Breaking the cumulative variance into partial sums, the first dimension justifies 55.01%, while the remaining 39.4% are allocated to the second dimension. Subsequently, a scatter graph was generated representing the dimensions mentioned above. Dimension 1 is illustrated by the X-axis and Dimension 2 on the Y-axis as shown in Figure 9.

Figure 9: Perceptual Map attributes' positioning



In order to further understand the scatterplot, more specifically, the correlations between variables and factors, factor loadings are examined, indicating the loading pattern to figure out and which component has the most impact on each variable. Loadings closer to -1 or 1 imply that the factor significantly impacts the variable. On the contrary, variables and loadings closer to 0 suggest that the factor has a minor impact on the variable (DeCoster 1998). An alternative to analyzing the factor loadings table is to observe the closeness of the vectors to the axis, where it is recognized that there are two-dimension groups as visible above. The first one shows a strong aggregate on Design and Style, Service Quality and Sophistication, Platform Reliability, and Items Quality. Whereas the second-dimension group, less evident, comprised the following variables: Sense of Community, Price Convenience and Fun and Entertainment. These groups fall into two distinct areas of perception characteristics, the first one directed to the attributes and the services/products provided on the apps, and the second one, encompassing the users' involvement with the second-hand fashion applications.

Figure 10: Perceptual Map platforms' positioning



Moving onto Figure 10, the aspect being analyzed is the position of the four platforms in the cartesian plane, which will serve as a function of dividing the four sections into quadrants.

These will be identified by using Roman numerals I, II, III, and IV beginning with the top right quadrant and moving counterclockwise. If the study subjects share a similar position in the plot, they are perceived to have similar profiles.

As it is possible to notice through their allocations, the platforms can be divided into three groups: Vinted positioned in the I quadrant, Depop in the III quadrant and Zalando Second Hand and Vestiaire Collective in the IV quadrant. Based on the consumers' evaluations, Zalando Second Hand and Vestiaire Collective, being in the same quadrant and relatively close, are easily comparable. This aspect implies that the apps are recognized to possess relatively matching qualities, indirectly increasing competition among them. On the other hand, as per Vinted and Depop, their profiles are depicted as unique due to their peculiar locations, which help them stand out from their adversaries. Lastly, one further observation that should be taken into consideration when analyzing the perceptual map graphs is the clear gaps that can be seen in the II quadrant, where none of the apps being evaluated is positioned in.

This information could be of strategical use as this evident gap plus other not so noticeable, such as the areas between the platforms within the quadrants, could represent an opportunity since no other company is perceived to be offering such a combination of specific benefits and features.

Figure 11: Perceptual Map platforms' positioning

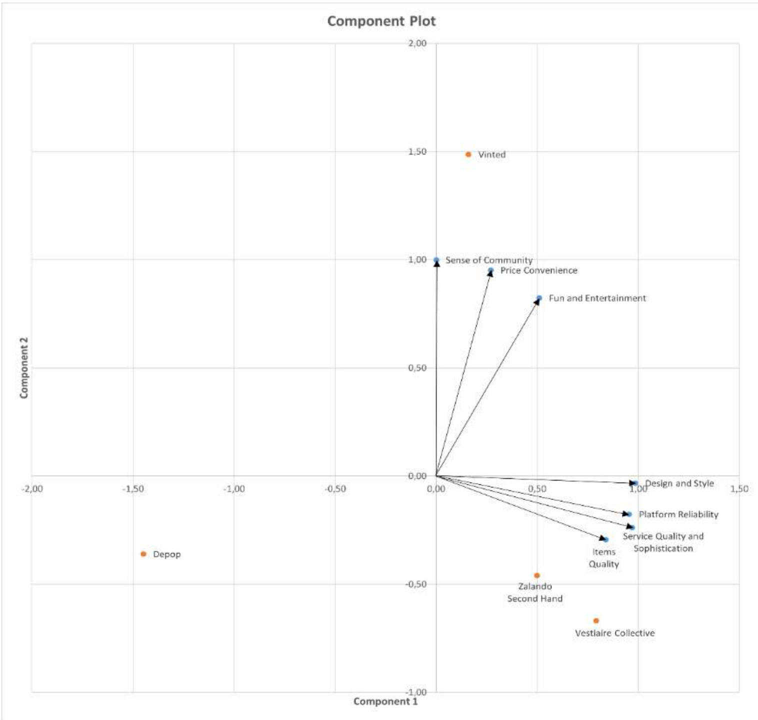


Figure 11 will merge the previous Figure 10, showing the companies positioning, with the positions associated with the seven pre-determined attributes used to evaluate the platforms with Figure 9 (Price Convenience, Items Quality, Platform Reliability, Design and Style, Fun and Entertainment, Service Quality and Sophistication, and Sense of Community). We can then interpret the graph using the lengths and directions of the vectors. First, it is possible to identify two clusters of attributes: one includes Sense of Community, Price Convenience, and Fun and Entertainment, while the second includes Design and Style, Platform Reliability, Service Quality and Sophistication, and Items Quality. Given the similar directions described by these two clusters, it is possible to identify positive correlations between the considered attributes, which implies that if one of them is rated high, a similar score can be expected for the other ones in the group. In this case, a high rate in sense of community will implicitly cause a high rate in both price convenience and fun and entertainment, and vice versa; the same logic can be applied to the other cluster, so a high rate in design and style would imply a high rate in reliability, items quality, and service quality and sophistication, and vice versa. It is relatively predictable that Items Quality, Service Quality and Platform Reliability are somehow correlated since they are all measures for quality. However, it is interesting to see that the Design and Style attribute is also potentially correlating with these perceptions.

Two further considerations are that, if the attributes directions are opposed one to another, it means that the attributes are negatively correlated. This implies that a high rate in one attribute is negatively associated with the opposite attribute, and vice versa. However, in this case, it is not possible to observe such a phenomenon as there is no opposite vector portraited. Addtionally, if the directions are perpendicular to one another, it implies that the attributes are uncorrelated. This can be observed in the following grouping: Sense of Community – Design and Style; Price Convenience – Service Quality and Sophistication. The practical implication of this observation is that, for example, sense of community does not affect Design and Style perceptions. Similarly, Price Convenience does not influence Service Quality and Sophistication.

Next, the vectors' angles illustrate an overlap in consumers' perceptions, implying that platforms linked to one feature will also be associated with another that presents a similar inclination. In this specific scenario, it is possible to group Platform Reliability, Items Quality, and Service Quality and Sophistication. However, Design and Style presents a moderately different slope, so it would not fit the group entirely. To a certain degree, this can also be applied to Sense of Community, Price Convenience, and Fun and Entertainment, even though the differences between the inclination is slightly more prominent compared to the first group identified. Moreover, the higher the value attributed to this factor, the more the attribute can distinguish between the brands considered. In fact, the attributes with the longest vector are Sense of

Community, Design and Style, and Service Quality and Sophistication, while the shortest are Items Quality and Fun and Entertainment, and based on that, it is possible to conclude accordingly.

After this review, it is possible to proceed with the merged analysis of the attributes and the platforms based on their positionings on the plane. Starting with Zalando Second Hand and Vestiaire Collective, as was previously mentioned, they present nearly identical profile characteristics. Their location can be explained by associating them with high reliability, quality of items sold, and satisfying service quality and sophistication. Interestingly, these two represent the B2C platforms among the platforms observed. Along with this goes, a high degree of buyer protection and the option (at least for Zalando) to return items, which could have caused the associations. The other two platforms, Vinted and Depop, as already noted, they occupy unique positions on the map. For Vinted, a positive association between price convenience, sense of community, and fun and entertainment must be remarked. These associations can be explained by the fact that, as a C2C platform, the need for a feeling of belonging and enjoyment of the purchase process are important for the success of a platform and Vinted has taken advantage of them quite well, giving it the opportunity of defining a strong community under the common objective of "getting rid of unused objects". For Depop, it seems to be negatively associated with the attributes following the x-axis and, to certain degrees, uncorrelated to the attributes following the y-axis. These negative correlations/uncorrelations portraited for Depop could be explained by referring to the ambiguous positioning it occupies. The app wants to convey a premium image (e.g., starting as a social network for creatives and art and design enthusiasts and moved to a reselling platform for such an audience), comparable to Vestiaire Collective and Zalando (B2C), but is formally a C2C. The fact that it does not implement quality checks on the products sold and get a percentage over sales (common practice for B2C platforms) might be a counterproductive practice for a C2C platform and can cause underappreciation as users/consumers do not perceive such an added value.

Another evaluation that can be performed is to rank the seven attributes per platform so that it is possible to explain more in detail the placements they cover on the map. The method used is to set a hypothetical perpendicular line on each one of the attributes lines and move it starting from the outside towards the inner part of the plane (i.e., the origin). The strength of the association will be based on how high the raking is, so the higher, the stronger. For example, Vinted ranks high on Sense of Community, Price Convenience, and Fun and Entertainment. On the other hand, Vestiaire Collective ranks high in Items Quality, Service Quality and Sophistication, Platform Reliability, and Design and Style. Zalando Second Hand is the closest second to Vestiaire Collective in all these previously stated attributes.

1.6 Conjoint Analysis

Moving away from the perceptions of the brands towards the preferences of the platforms and platform attributes from a functional and feature perspective, the following chapter will deal with conjoint analysis in the secondhand platform industry.

Firstly, we are going to brief the attributes to test in conjoint analysis. Secondly, we are going to analyze the results of the conjoint questionnaire. The sub-chapter will start with the analysis of the sample characteristics moving on to the brand preferences, followed by the attribute importance and the partworth utility analysis of the attribute levels. Then, a correlation analysis will be conducted to identify relationships between highest ranked attributes with the sample characteristics and their buying motives. Finally, we will create counterfactual scenarios to allow further insights on market dynamics.

1.6.1 Methodology

For the conjoint part of the analysis, we followed the process provided by Rao (2019). As such, the first step represented the choice of attributes and levels as further outlined below.

<u>Attributes and Levels</u>

The attributes to test were chosen based on their relevance within the literature and the preliminary interviews that were conducted in the beginning. Here, we have mainly taken the findings of the interviews with the consumers into account. As such, as analyzed in chapter 1.3.5 the attributes price, variety, trust mechanisms (e.g., buyer protection, payment ecosystem), delivery service quality and ease of use, analyzed in the literature review, were confirmed by the interviews with the consumers. However, it must be noted that delivery service quality is not clearly distinguishable from trust mechanisms, since it impacts the way, users trust in a platform. If the delivery is not reliable, trust can be eroded preventing the user from continuing to use the platforms.

The selection of attributes has been conducted through multiple review stages starting with initially 12 reducing them to 7 final attributes to test. The reduction has mainly been conducted to increase the respondent friendliness. Ensuring the respondents would not be overwhelmed, by the large number of attributes, we acknowledged a common problem within full-profile conjoint analysis (Green and Srinivasan 1978; Mennecke et al. 2007).

The first draft discussed with the thesis advisor included the following 8 attributes: brand, delivery time, ease of use, reliability of information provided, buyer protection, payment options, product variety and fee per purchase. Based on the feedback received, ease of use and reliability of information have been eliminated as they could not be tested objectively, representing subjective impressions, not features. In addition, it can be assumed that both attributes have some relationship with other attributes, which would violate the need for independence between the attributes as outlined in chapter 3.4. Reliability for instance, might be influenced by the availability of a buyer protection mechanism, ease of use by the payment methods for example. In addition to the elimination of the two attributes, item price has been added as an additional attribute.

Finally, seven attributes have been selected for the conjoint analysis. Here, it was assured that all attributes are non-overlapping and except for the item price and the fees with the other attributes, independent from each other. Table 4 below presents an overview of the chosen attributes and their respective levels.

Table 4: Overview over Attributes and Levels

Attribute	Attribute levels	Source
1) Brand	• Vestiaire Collective • Zalando Pre-Owned • Vinted • Depop	Blasigh 2015; Naef 2021; Similarweb (Appendix 4.1.1)
2) Variety	• Offering only one type of fashion (e.g., only Fast Fashion, Vintage or Luxury) • Offering all types of fashion	Lee et al. 2021; Alanadoly and Salem 2022
3) **Price**	• 5€ • 15€ • 30€ • 50€	Laitala and Klepp 2018; Guiot and Roux 2010; Seo and Kim 2019
4) **Buyer protection**	• Platform guarantees return and reimbursement in case of fraud or delivery of a faulty item • Platform does not guarantee return and reimbursement in case of fraud or delivery of a faulty item	Lu, Zeng and Fan 2016; Lu, Fan and Zhou 2016; Lu and Zhang 2020
5) **Delivery services**	• Express delivery in 24 hours • Premium delivery in 2-5 working days • Basic delivery in 5-10 working days	Bienstock and Royne 2010; Bouzaabia et al. 2013; Mentzer and Flint 1999; Mentzer et al. 2001
6) **Additional fee /purchase**	• Free • 2,99€ • 4,49€ • 5,99€	Tranquillini 2021; https://www.vinted.com/
7) **Payment options**	• Basic: Credit Card + PayPal • Advanced: Credit Card + PayPal + Credit on the platform from your previous sales	UPS Inc. 2019; https://www.vinted.com/ ;https://blog.depop.com

In the following, the reasoning for the inclusion of the attributes and the attribute levels will be given.

1) For the brands attribute, the four platforms subject of the thesis are presented. The brand attribute was included because of its potential impact on the decision for or against certain profiles. As stated in Chapter 1.2.4, the brands have been chosen due to their importance in the Italian market.

2) The variety attribute focuses on fashion category variety, i.e., the platform offers a certain type of fashion (e.g. vintage, fast or luxury fashion) or all types of fashion. Initially, also other variety attributes, such as market variety in a sense that products can also be bought from other countries, have been considered. However, the variety attribute related to the fashion category was seen as the most fundamental one, as it partly also distinguishes the platforms tested from each other, e.g., Vestiaire Collective with a focus on luxury or Vinted with no specific focus on a certain type of fashion.
3) The product price attribute was included due to its potential impact on the choice of other attributes. It might happen for instance, that the product price has an impact on the willingness to pay for an additional fee. In addition, to provide a realistic decision situation, it is necessary to include the price in the profiles. The different price levels were chosen representing a relatively realistic spectrum, aiming also to include a close to realistic price for Vestiaire Collective, whose price level clearly exceeds the one of the other platforms. It is also assumed, that the span covered is large enough to depict potential impacts of different product prices on the choices.
4) The buyer protection attribute was included based on the importance of trust within the marketplaces retrieved from the interviews and the literature review. The platform taking the responsibility for fraud and the delivery of faulty items is assumed to drastically increase the level of perceived security and drastically reduce the financial risk as outlined in Chapter 3.5.
5) The delivery service quality attribute was included through the delivery time. While delivery service quality has many facets as outlined in Chapter 3.5, the complexity was reduced through the choice of delivery time enabling clearly distinguishable attribute levels.

6) The attribute additional fee per purchase was included to test the willingness to pay extra for the usage of the platform, considering an estimated amount the buyers will have to pay if they choose buyer protection and different levels of delivery speed. In addition, it allows a comparison of consumer price sensitivity between the item price and the additional fee. The levels were based on realistic delivery fees on Vinted in Italy, the in Chapter 1.2.4 described buyer protection fees on Vinted, and on a combination of both (Tranquillini 2021). A "free" attribute level was included considering that Zalando ships secondhand item exceeding a value of 24,90€ for free and allows return of the secondhand items bought, which makes the buyer protection obsolete for the company.[8]
7) The payment method attribute was included due to the importance identified in the interviews and the literature review. Here, credit card and PayPal have been chosen due to their relevance in Europe (UPS Inc 2019). However, as some of the platforms, e.g., Vinted and Zalando, as described in chapter 2.3 also do offer the option to use credit from previous sales as means of payment, this option was also included.

The order of the attributes was chosen based on the realistic yet slightly simplified consumer journey on the platform. As such, the attributes within the survey are presented in the same order as they appear when the consumer visits the platform and decides to buy a certain item, as briefly explained in the following. When the buyer opens the platform, they are initially being confronted with the brand of the platform. Subsequently, he or she will see the variety of the clothes when scrolling through the offer alongside with the price for each item. Then, on the product page, the buyer is confronted with the option to buy. In this context, typically also the information on the buyer protection appears. Nearby, also the information on the shipping

[8] https://www.zalando.it/

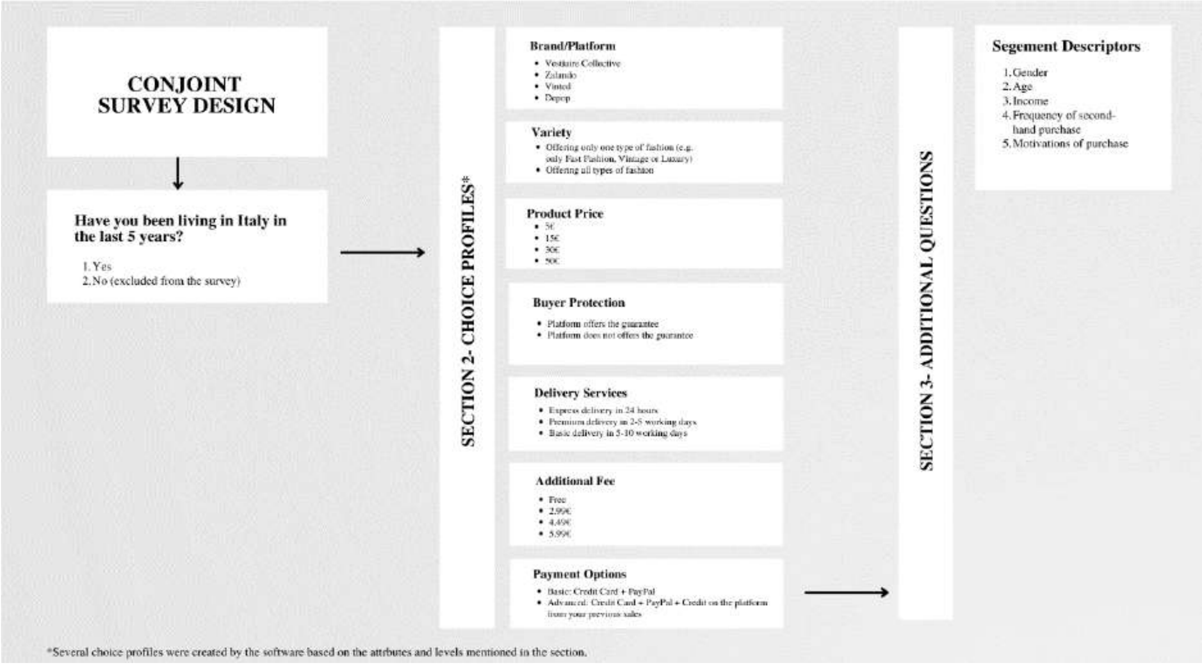
is presented. As the additional fee is comprised of delivery fee and buyer protection, it is presented below both attributes. Finally, the payment options are presented as last attribute since it represents the last step in the purchase process.

Initial Survey Setup in Conjoint.ly

As stated in chapter 1.3.4, for this work project, the conjoint format of choice-based conjoint was chosen in order to confront the respondent with a choice, that is as close as possible to a real-life decision-making scenario. For the setup of the study, the software Conjoint.ly was used. The platform is an all-in-one survey research platform and has specialized on easy usage advanced tools originating from offering conjoint analysis only. Conjoint.ly was chosen for its fast and easy usage and the intuitive survey design, also from the respondents' perspective. It allows an automated translation to the respondents' language, which with some manual adjustments was used to provide the survey in Italian to the sample.

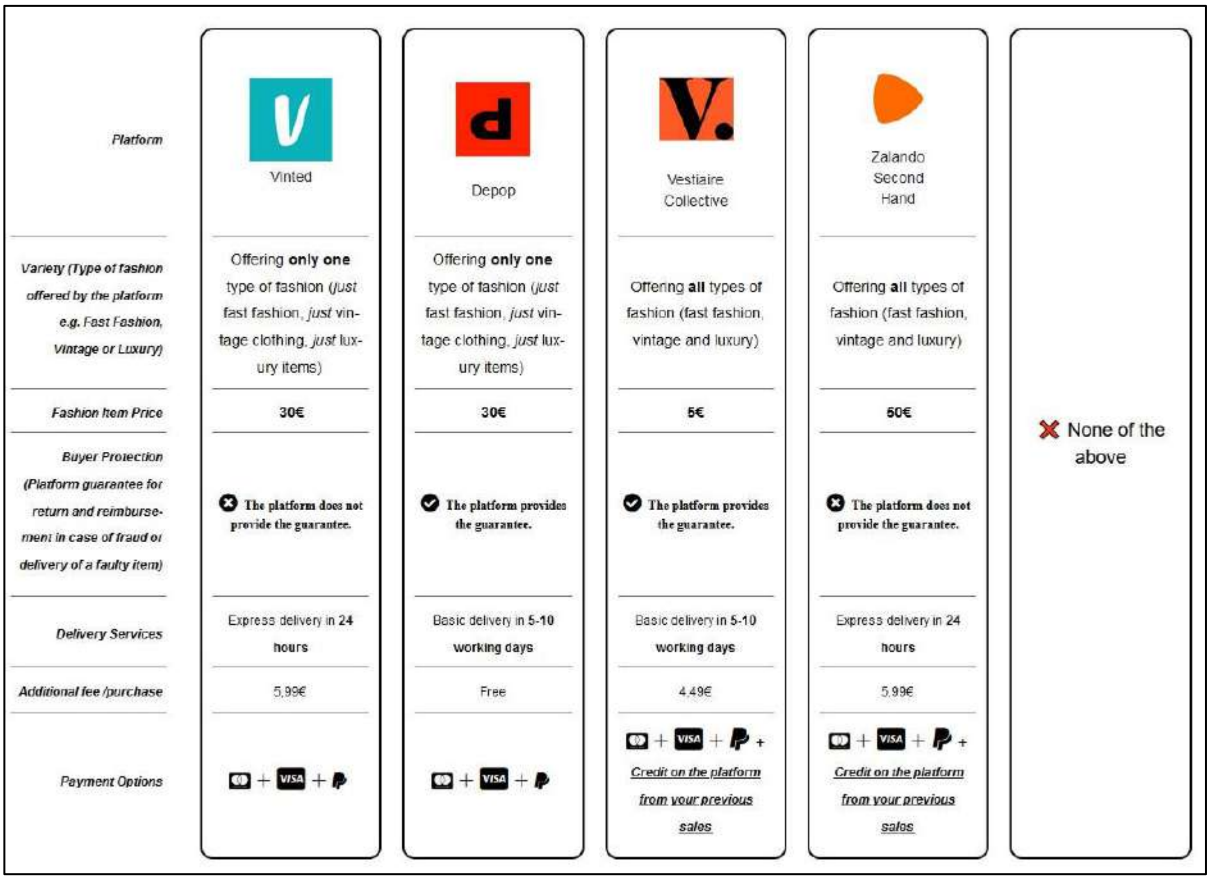
As for the survey layout, an additional question was added in the beginning of the survey to ensure that people who have been living in Italy from past 5 years continue with the rest of the study. Respondents who selected "no" were immediately excluded from the sample. After the first step, the choice-profiles randomly appeared based on the attributes and levels added in the setup. Lastly, some additional questions were asked from the respondents to know about their sociodemographic and motivations to buy from secondhand platforms. See Figure 12 below for an overview of the survey design.

Figure 12: Conjoint Analysis Survey Design (Overview)



As for the design, a brand-specific conjoint was chosen on the software, allowing to test not only features and claims like in the generic conjoint option, but also price. After all the attributes and levels have been included in the brand-specific conjoint survey, all combinations of attributes and levels have been allowed. Furthermore, a no-choice option has been included in the setup. The number of profiles the respondent sees simultaneously has been set to four, according to the four brands tested. In each decision, each brand appears once. The total number of decisions to be made by the respondent is twelve. For the layout, where applicable, logos and icons have been included to provide a more lively and less tiring experience as seen in Figure 13.

Figure 13: Layout of the Choice Sets within Conjoint.ly



<u>Additional Questions</u>

The core of the conjoint survey, which is the presentation of the profiles, was surrounded by additional questions. The same demographic and behavioral questions as in the survey for perceptual maps have been included in order to understand about the interference between the preferences and the demographic and psychographic factors of the sample, also understanding differences in preferences between the personas defined in chapter 1.3.7. All in all, the survey consisted of eight additional questions and twelve decisions related to the conjoint measurement.

Pre-Test and Data Collection

Before the official launch of the survey, it has been tested among Italian friends of ours. Based on the feedback, some changes on the information provided have been made increasing clarity and respondent friendliness. In addition, as the test respondents pointed out the high level of concentration needed to finish the survey, especially due to the presentation of the profiles one below the other in the mobile version of Conjointly, which might result in a high number of early terminations of the survey, the authors decided to include the raffle of a 50€ Amazon voucher as additional motivator to complete the survey.

The survey has been open for six days from the April 1st 2022 to April 6th 2022. The distribution channels, synchronous to the survey on perceptual maps have been LinkedIn, Facebook, Instagram and WhatsApp. Here, the survey was distributed on personal social media accounts as well as within family and friends' groups. Moreover, also social media groups dedicated to research and second-hand clothing have been used, e.g. "Vestiaire Collective Italia" or "Zalando Italia".

1.6.2 Results

Sample Characteristics

The following results are based on the sample of 112 respondents of which 6 have been excluded due to lack of quality of their responses. Visual presentations of the sample distributions based on the factors gender, age, education, income and frequency of purchase can be found in Appendix 11.4.1.1.

Of the 106 respondents taken into account, 67% have been female, 30.2% have been male and 2.8% preferred not to disclose their gender. In the Italian population, in 2021, approx. 51.3% were females as opposed to approx. 48.7% males (ISTAT 2022).

As for the age distribution, there was a clearly stronger representation of young people with the age class of 16 to 25 accounting for 56.6%, followed by the age class of 26 to 35 with 25.5%, 36 to 45 years with 9.5% and 45+ years with 8.5%.

In regard to education level, the sample is relatively evenly distributed with 30.2% of respondents having completed high school or less, 34.9% having completed a bachelor's degree and 34.9% having completed a postgraduate degree. As compared to the overall Italian population, the sample is strongly skewed towards highly educated people. According to the national statistics institute in Italy, in 2019, 14.96% of the people older than 15 years held a university degree (ISTAT 2020). However, it is worth considering that the sample is also younger than the Italian population, which most likely implies that it is more educated (ISTAT 2020).

Looking at income levels, the largest group is represented by people earning less than 800€ with 38.7%, followed by the class from 800 to 1.500€ with 29.2%, the class from 1.500 to 2.000€ with 27.4% and the class from 2.000 to 3.000€ with 4.7%. With a mean monthly income of approx. 1.087€, the sample mean clearly falls below the average monthly income in the Italian population amounting approx. to 1.817 € in 2020 (Ruffino 2021). This might be due to the young age of the sample, as younger people typically have a lower income than older ones.

With regard to the frequency of purchase of secondhand items, the large majority (83%) of respondents has bought 3 items or less in the last three months. 13.2% of the respondents have bought between 4 and 6 items, while 3.8% have bought more than 7 items in the last three months.

Considering the reasons of the sample to consume secondhand fashion, measured with a 5-point Likert scale with 5 representing the highest possible agreement and 1 representing the lowest possible agreement of the relevance of the certain reason, according to the mean, the most frequently named reason have been the "low prices" (3.7) , followed by "price / quality ratio” (3.6) and “finding unique items” (3.6), “sustainability” (3.4) and finally “buying designer and luxury brands” (3.1).

Taking the median into account, the same order is represented. However, the differences between the importance of the different reasons seem to be rather small. Interestingly, economic reasons play a larger role in the sampling than sustainability. The fact that “buying designed and luxury brands” is the least important reason is expected, due to the smaller market volume of the luxury market as compared to the overall apparel market (Statista 2022a; Statista 2022b).

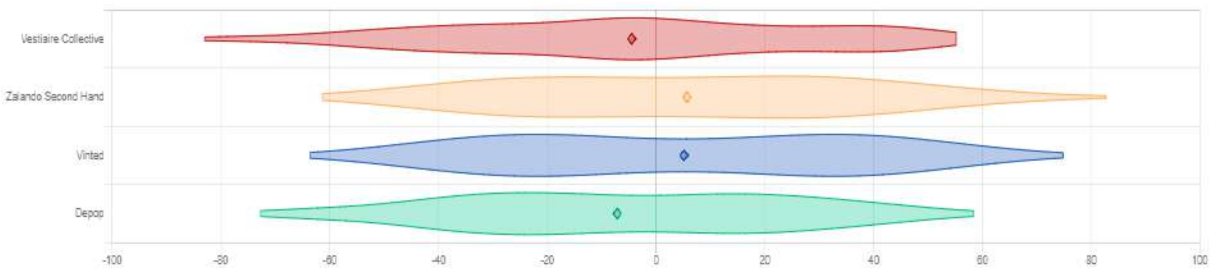
Conjoint Survey Results

The following analysis of the results for the conjoint analysis will be based on the report provided by the Conjoint.ly software itself, including the most preferred platform, attributes, and levels on average by the respondents (Conjoint.ly 2016a). In addition, we will create simulations to support our findings for attribute preferences across all platforms and evaluate the variance in the preferences as we change the market scenarios.

Brand Preference & Ranked Concepts

The brand preference graph (see Figure 14 below) gives us an estimate about on average how strongly customers prefer different brands of online second-hand clothing, considering the different variants (combinations of features and prices) presented to them in the survey. The center diamond on the graph shows the average preference for each brand, and the regions in the form of different violin shapes are the estimated distribution of the data.

Figure 14: Brand Preference (based on average responses)



In this graph above, based on the average responses and their corresponding mean values, it shows that Zalando (5.7) and Vinted (5.1) tend to have more appealing variants than Vestiaire Collective (-4.5) and Depop (-7.1). In conclusion, among all, Zalando is the most preferred platform followed by Vinted. The reason for this difference is because the consumers near the far right, have a stronger preference for Zalando, potentially showing some brand loyalty, this might result in a higher willingness to pay. This fact is also reflected in the top ranked product concepts given in the survey report (See Figure 42 in Appendix). These concepts are the list of all the possible combinations shown to respondents and ranked according to the consumers most preferred choice profiles.

The ranking is based on the relative performance of the levels that were combined, which makes it possible to know the construct of the best option for customers that they prefer the most over others. It revealed that many people showed willingness to pay 15€ when it appeared with Zalando and for Vinted people mostly preferred to pay 5€, which later can be also seen in the highest partworth utilities of product price levels for each of these brands. Moreover, the top 10 ranked concepts showed on average people in the sample possibly have low to willingness to pay (from 5-15€) compared to the higher prices (30-50€), which mostly emerged with Depop and Vestiaire Collective. It also explains the reasoning for Depop and Vestiaire Collective to be ranked lowest (in 30+ of the list) preferred brands. To further highlight, Zalando and Vinted were the only brands who appeared in the first top 10 ranked concepts (6 and 4 times respectively). Whereas, as mentioned earlier Depop and Vestiaire Collective only started to appear in the following 30 concepts, although the combinations of attributes were similar to the highest ranked concept except changes in product price (30€). This shows that for the brands like Zalando and Vinted consumers are in general perceiving the combination of the other attributes such as buyer protection, additional fees etc. within a lower price range as better deals (see Figure 42 in Appendix).These are the following top three preferred combinations for the consumers: 1st most preferred combination consists of Price 15€, a platform offering all types of fashion (Fast Fashion, Luxury, and Vintage), Platform offer the buyers protection, Express delivery in 24 hours, Free additional costs, and Advanced: Credit Card + PayPal + Credit on the platform from your previous sales. The second-best alternative is to replace advanced payment options with basic one, and in the third-best scenario opt for a lesser price of 5€ and keep the rest of the attributes equal to the highest-ranked concept.

Relative Importance by Attribute

To see the attribute's importance (attribute-partworths), all the values assigned to each attribute sums up to 100%, which means it is calculated to check the relative importance of each attribute over the other. These results are influenced by the range of preference given to the levels within the attributes by each respondent. For example, if in our conjoint survey an additional level of product price was added in the price attribute – let's say 80€ – respondents would have most likely avoided it, and as a result, the partworth of that level would have been very negative, inflating the relevance of the entire price attribute.

Table 5: Attribute Importance of each Brand

	Vestiaire Collective	**Zalando**	**Vinted**	**Depop**
Variety	8.4%	6.6%	7.6%	4.4%
Product Price	28.0%	26.5%	26.3%	28.4%
Buyer Protection	23.7%	27.1%	29.9%	23.9%
Delivery Services	8.2%	13.8%	13.9%	13.1%
Additional Fee	26.1%	19.5%	17.8%	23.8%
Payment Options	5.6%	6.4%	4.6%	6.5%

According to the attribute partworths (see Table 5 above), Buyer Protection has emerged as one of the most important attributes in the case of Zalando (27.1%) and Vinted (29.9%), whereas product price is shown as the most important concern for the consumers of Depop (28.4%) and Vestiaire Collective (28%). Additional fees stood as the third most important factor in the case of Depop (23.8%), Vinted (17.8%), and Zalando (19.5%), but for Vestiaire Collective (26.1%) it was the second most concerning attribute for users. To sum up, product price, buyer protection, and additional fees are the top three attributes across all the platforms, with relatively higher significance (collectively more than 70%) than the rest of the attributes such as variety, delivery services, and payment options (see Table 5 above). To note, payment options was the least preferred attribute by the respondents – 5.6% in Vestiaire Collective, 6.5% in Zalando, and 4.6% in Vinted. For Depop, variety (4.4%) was the least valuable characteristic.

Relative Importance by Level

Again, the level partworths (See Table 34 in the Appendix and following tables in this section for each attribute) are calculated relatively. For instance, even in this case if one more level was included in the attribute's levels, it would have influenced the relative value of rest of the levels. The values assigned to each level are based on average preferences. The levels that have highest preferences by the consumers are given the highest values and vice versa. During the analysis of the partworths, the levels are scales such that the sum of all positive values (highest-preferred) equals to the negative values (lowest-preferred).

Table 6: Partworth utilities of all the brands - Product Price

Attributes	Levels	Vestiaire Collective	Zalando	Vinted	Depop	Average across the platforms
Product Price	5€	4.1%	3.2%	10.0%	5.7%	5.8%
	15€	3.1%	11.1%	5.4%	2.7%	5.6%
	30€	8.0%	(2.1%)	(4.4%)	7.9%	2.4%
	50€	(15.2%)	(12.2%)	(11.0%)	(16.4%)	(13.7%)

Based on the average partworth utilities of product price across all platforms (see Table 6 above), products worth of 5€ and 15€ are most preferred by the average respondents (5.8% and 5.6% partworths respectively). The product prices 30€ and 50€ are the least preferred prices. We have taken an average of the partworth utilities of product price, since we observed discrepancy in preference of product price levels across the platforms – this allowed us to know the overall price preference of the second-hand consumers.

However, on the extreme of the comparatively lower price range (5-15€), we observed a set of brands with similar patterns like each other – Zalando and Vinted, but with changes in their top priority product price levels. The respondents showed the highest willingness to spend 15€ on Zalando (11.1%), across all the brands (see Table 6 for partworth utilities of product price) and on Vinted they showed the most likelihood of spending 5€ (10.0%). It is interesting to note that their second preference was to choose either of these product prices, meaning for Vinted, people prefer to pay 15€ (5.4%) and for Zalando, they showed some willingness to spend 5€ (3.1%), but respondents did not really show any inclination for paying 30 or 50€ for these brands. This brings up the possibility that people, in general, have a low willingness to spend on second-hand clothing platforms (Chapter 1.3.5), as previously seen these platforms are the most preferred brands.

On the other end, we observed that Vestiaire Collective and Depop consumers showed the highest preference to purchase a product worth 30€ (having partworth utilities of 8.0% and 7.9% respectively) as compared to Zalando and Vinted (-2.1% and -4.4% respectively for 30€). Another similar pattern of reaction was observed for both Vestiaire Collective and Depop, which was in the case of the lower product price options; 5€ was the second preferred option for both Vestiaire Collective (4.1%) and Depop (5.7%), although it still has a somewhat significant difference from the top-preference utility (30€). Another interesting observation for us was that 50€ was the least preferred level on all the platforms with the most negative part-worths.

Taking into consideration only the two most extreme preferred levels in product price (30€ and 5€), there could be several possible reasons for these patterns.

First, there could be a probability of some noise in the data which might have influenced the average results. This could be also due to the likelihood that people were not attentive towards the prices shown to them during the survey. As it is previously seen in several conjoint studies that people might start finding the survey tiresome (Chapter 3.4). Yet, while constructing the survey combination limit, this issue was kept under consideration (Chapter 6.1).

As explained later, in contrast to preferences on prices, consumers react to additional fees in a more predictable manner. This suggests that the explanations above are somewhat unlikely to explain the patterns in the data, since noise in responses or lack of attention should have similarly affected the responses to additional fee. Instead, we hypothesize that some participants may hold strong associations between price with quality and expect quality to be negatively associated with price (Zeithaml 1988). Hence, consumers may have perceived the question related to product price that “what is a reasonable price for this product” rather than “how much are you willing to pay for it?”. We focused on the extreme levels of the price attribute, to see at which point willingness to pay overwhelmed consumer’s “price appropriateness”- which in this case was 50€, since a slight preference for 30€ was shown.

It is also important to underline the fact that as mentioned in chapter 1.2.4, for example, Vestiaire Collective is considered the premium French brand, and Depop is a platform for vintage clothing which are not usually available at lower prices, therefore there might be a possibility that few respondents were already aware of these brands and did not hesitate to opt a slightly higher price (more than 5-15€) - when shown these platforms with 30€ worth of product, after recalling their experience and the type of variety these platforms normally have (e.g. Vintage and luxury). On the contrast, participants showed most preference of 5€ on Vinted, which brings up the possibility that they assume to find the products that are worth 5€ such as casual T-shirt or a summer tank top on this platform. Hence, this tells that there might be an additional possibility that the consumer’s responses were influenced when they encountered any platform that they were familiar with.

Table 7: Partworth utilities of all the brands- Buyer Protection

Attributes	**Levels**	**Vestiaire Collective**	**Zalando**	**Vinted**	**Depop**
Buyer Protection	Platform offers the guarantee	17.5%	17.8%	20.6%	18.3%
	Platform does not offer the guarantee	(17.5%)	(17.8%)	(20.6%)	(18.3%)

As mentioned in the literature (chapter 1.3.5), people generally are afraid of fraud on online platforms, therefore they do not easily trust these platforms, but recently dispute resolution mechanisms such as "buyer protection" have been playing an important role in improving the sense of overall secure experiences on these platforms. This reasoning could be the possibility why respondents showed a high preference in choosing a platform that offers a guarantee (buyer protection) (see Table 7 above). As mentioned earlier, for the platforms Zalando and Vinted buyer protection was the top preferred attribute, with 17.8% and 20.6% partworth utilities for having a platform that offers a guarantee. Additionally, we see that although for Depop and Vestiaire Collective buyer protection was not the top priority but still was among the top three with having the partworth utilities (platform offers the guarantee) of 17.5% (Vestiaire Collective) and 18.3% (Depop), which are also close to the partworths of Zalando and Vinted. Therefore, it shows buyer protection is considered one of the essential attributes of second-hand platforms by respondents, across all the platforms. Further, it is worth noting that Vinted and Depop have the highest partworth utilities for platform guarantee, which could be because some respondents might be aware of or have heard of these platforms, and their decisions were influenced by having the knowledge of what kind of buyer protection policies these platforms have. Additionally, people who are aware of these platforms, would also know that Vinted and Depop are C2C platforms, therefore they value buyer protection more on these platforms comparatively to the B2C platforms (Zalando and Vestiaire Collective).

Table 8: Partworth utilities of all the brands- Additional Fee

Attributes	**Levels**	**Vestiaire Collective**	**Zalando**	**Vinted**	**Depop**	**Average across the platforms**
Additional Fee/Purchase	Free	12.2%	12.7%	9.5%	12.8%	11.80%
	2,99€	10.6%	(1.0%)	2.8%	2.4%	3.70%
	4,49€	(3.6%)	(5.4%)	(7.6%)	(7.0%)	(5.9%)
	5,99€	(19.1%)	(6.3%)	(4.7%)	(8.1%)	(9.55%)

Another interesting outcome was about the additional fees being among the top three prioritized attributes for respondents when in a marketplace situation. Commonly across all the platforms, it was not surprising to see people preferring "Free" additional costs the most and remarkably higher than the rest of the levels (Vestiaire Collective 12.2%; Zalando 12.7%; Vinted 9.5%; 12.8% Depop) (See Table 8 above). However, we observed some inconsistency also in the preferred levels of additional fees across the platforms, hence we took the average across different levels to have an overview of the preferences. As we saw earlier, the level "Free" has the highest preference and also on average, it is the most preferred level (11.8% average partworth utility). Interestingly, we see that on average people have shown some willingness to pay additional fee of 2.99€ (3.7% average partworth utility) which is still quite low to interpret consumer's willingness to pay any additional fee. This might indicate the problem of monetization for these platforms on the consumer side.

As we saw earlier that for Vestiaire Collective additional fee was the second most important attribute and for the rest of the platforms it stood as the third priority, but with rather having less importance (see Table 8). The most interesting finding in this case is that respondents only showed a willingness to pay additional fees worth 2,99€ with 10.6% partworth utility for Vestiaire Collective- the highest amongst all the platforms. However, there was some willingness shown in the case of Vinted and Depop as well for an additional fee of 2,99€ with 2.8% and 2.6% of partworth utilities (respectively). For Zalando, people did not show any willingness to pay any of the additional fees (2,99€ (-1.0%); 4.49€ (-5.4%)). For the rest of the levels of additional fees (4,49€ and 5,99€) across all platforms, no significant inclination was shown (see Table 8).

Table 9: Partworth utilities of all the brands- Variety, Delivery Services, Payment Options

Attributes	Levels	Vestiaire Collective	Zalando	Vinted	Depop
Variety	Offering only one type of Fashion	(2.8%)	(3.8%)	(4.2%)	(0.6%)
	Offering all types of Fashion	2.8%	3.8%	4.2%	0.6%
Delivery Services	Express delivery in 24 hours	1.7%	7.2%	4.7%	6.5%
	Premium delivery in 2-5 working days	(1.1%)	(2.2%)	0.2%	(1.8%)
	Basic delivery in 5-10 working days	(0.6%)	(4.9%)	(4.9%)	(4.7%)
Payment Options	Basic: Credit Card + PayPal	(1.0%)	(1.2%)	(1.4%)	(2.9%)
	Advanced: Credit Card + PayPal + Credit on the platform from your previous sales	1.0%	1.2%	1.4%	2.9%

Lastly, delivery services, variety, and payment options (see Table 9 above) turned out to be the least significant attributes for the consumers across all the platforms. According to chapter 1.3.5, these attributes are considered valuable by the consumers and would most likely influence their purchasing decision. However, when they are combined with other much more important factors such as price and buyer protection, their importance might have been overshadowed. This concludes that these attributes, do not stand so strong in consumers' minds when in a trade-off scenario. Lu and Zhang (2020) also mention in their paper about online platforms that some attributes might not stand as important for buyers when they are making real marketplace choices, compared to when they are considered individually. In their analysis, Lu and Zhang (2020) also found delivery services (logistics) as the low-rated attribute for the consumers when choosing an e-commerce platform in a trade-off setup. Moreover, consumers might not directly consider it as part of the marketplace, but rather take it as a third-party service provided by the delivery options, they choose (Lu and Zhang 2020). Regarding the variety and payment

options, although the preference for them compared to other attributes were the lowest, consumers preferred to have all types of fashion on the platform, and also have wallet credit as part of the payment options available on these platforms.

In conclusion, it can be assumed that in general if the consumers find fair deals within a reasonable price range, they show willingness to do a trade on second-hand platforms (chapter 1.3.5). For example, in the case of Vinted respondents showed a slight willingness to pay an additional fee (2.8% for 2.99€) which might be due to the overall low average cost they would have to bare, meaning, if a consumer buys a product worth 5€ and pays an additional fee of 2.99€ (total of 7.99€), they would be still paying even lower than the average price preferred on Zalando (15€). This shows usually people are looking for deals that are convenient (have buyer protection, low additional fees, etc.) under a reasonable price (chapter 1.3.5).

<u>Correlation Among Variables and Highest-Ranked Attributes:</u>

In order to better understand our respondent's characteristics, some additional descriptive questions were included at the end of the conjoint survey such as age, gender, income, etc., and also a Likert scale question to learn about their motivations to buy from second-hand platforms. This information will further assist us to evaluate the variance in consumers' attribute preferences on different platforms with various motives and sociodemographic. For instance, it can allow us to identify any influence of age or income on the product price or preference for buyer protection, etc. To analyse the relationship between these variables and attributes, we investigate cross-correlations across attributes. We focus on the topmost preferred attributes across all the four platforms are used (Buyer Protection, Product Price, and Additional Fee) to investigate their relationship with the variables.

First, to identify any significant correlation among the descriptive variables themselves, we conducted the cross-correlation test within the descriptive variables only. For example, (see Figure 15 below) a strong positive correlation was found between age and income, which means as the age increases most likely the income of our respondents also increases. This is sensible to assume since typically, wealth is positively associated with age.

Figure 15: Correlations within the variables

Variables	Gender (Male=1)	Age (1-4)	Education (1-3)	Income (1-4)	Frequency (1-3)	Lower Prices	Price/Quality Ratio	Finding Unique	Buying designer	Sustainability
Gender (Male=1)	**1**	0.057	-0.115	0.013	-0.111	-0.023	0.005	-0.184	**-0.322**	-0.142
Age (1-4)	0.057	**1**	-0.104	**0.531**	0.094	-0.022	0.117	-0.087	0.106	-0.060
Education (1-3)	-0.115	-0.104	**1**	0.077	0.119	-0.143	0.110	0.074	0.129	0.113
Income (1-4)	0.013	**0.531**	0.077	**1**	0.050	-0.177	-0.037	0.023	0.126	**-0.254**
Frequency (1-3)	-0.111	0.094	0.119	0.050	**1**	0.140	0.164	**0.239**	**0.266**	0.167
Lower Prices	-0.023	-0.022	-0.143	-0.177	0.140	**1**	**0.345**	-0.069	-0.176	**0.363**
Price/Quality Ratio	0.005	0.117	0.110	-0.037	0.164	**0.345**	**1**	0.075	0.122	**0.268**
Finding Unique and Cool Items	-0.184	-0.087	0.074	0.023	**0.239**	-0.069	0.075	**1**	**0.316**	0.039
Buying designer and Luxury brands	**-0.322**	0.106	0.129	0.126	**0.266**	-0.176	0.122	**0.316**	**1**	-0.129

Values in bold show a weak to medium correlation with significance level α =0.05

Moreover, there is a negative correlation between males and the motivation to buy designer and luxury clothes on secondhand platforms, which could mean that they are not looking for buying luxury second-hand items on these platforms.

Further, there is a negative correlation between income and sustainability, which means that as income increases, people are less concerned about sustainability, which was interesting to observe since some studies have reported people showing concerns for sustainability when they have higher incomes (Fisher, Bashyal and Bachman 2012). Another significant correlation was seen between sustainability with lower prices and the price/quality ratio. There is a positive correlation among them, which might mean that people who have these motives are looking for low-priced but good quality secondhand items at a reasonable price and also believe that they are contributing towards sustainability by using these reselling platforms.

Interestingly, the consumer's inspiration for finding unique and buying designer clothes on reselling platforms are positively correlated with the frequency of purchase, which could mean the frequent consumers of these platforms have a high motive to find unique pieces and designer clothes.

Further, to evaluate the impact of these variables across the different platform's most important attributes, we have conducted a correlation matrix with each brand. The correlations that are found highly or somewhat significant are discussed in the results (see Table 10 below):

Table 10: Correlations of variables with highest-ranked attributes

	Vestiaire Collective	**Zalando**	**Vinted**	**Depop**
Product Price	(-) Age (-) Price/Quality ratio	(+) Lower prices (+) Price/Quality Ratio	(-) Age (-) Income (+) Lower prices (-) Buying branded clothes	(-) Age
Buyer Protection	(+) Frequency of Purchase (+) Buying designer clothes (+) Finding unique and cool items	(+) Income (-) Lower prices	(+) Income (+) Frequency of Purchase (+) Buying designer and luxury clothes	(+) Frequency of Purchase (+) Buying designer and luxury clothes (+) Finding cool and unique items
Additional Fee	(-) Finding unique cool items	(-) Income (-) Age	(-) Age (-) Frequency of Purchase (-) price-quality ratio (-) buying designer clothes	(-) Income (-) Buying designer clothes

First, we identified a common observation across most platforms that the consumers from the upper age group show less importance to the product price. This may indicate that the preference for product price does not have much relevance for the respondents who belong to the upper age group and vice versa.

Further, we see that lower price and the importance of product price in Zalando and Vinted are positively correlated, meaning there is a chance that the consumers who have a high motivation of finding low-priced items on these platforms, prefer the product prices of Zalando and Vinted. It can be assumed that people find Vinted and Zalando relatively low-priced platforms.

There is also a slightly positive relationship between the price/quality ratio and the product price of Zalando, which supports that people who might have preferred the product price of Zalando, are not willing to spend more on second-hand clothing and are looking for low prices but with relatively good quality clothes- considering they are second-hand. However, the Price/Quality ratio has a slightly negative correlation with the Vestiaire Collective product price, which might signify that those consumers who have a low intention for the price/quality ratio, might have a relatively high willingness to pay while using Vestiaire Collective, and vice versa.

Furthermore, a significant negative correlation was observed between the preference for product price of Vinted and buying designer items. This might imply that consumers who are looking for designer or luxury clothes do not find the Vinted product prices preferable. Therefore, it could be possibly concluded that consumers perceive Vinted as a low-cost platform where they might not go to find second-hand designer clothes, which usually are more expensive.

Moreover, we commonly identified across several platforms that the frequent users of reselling platforms or the consumers who are looking for branded and unique clothing items prefer to have buyer protection as part of their trade. Another interesting observation is that in the case of Zalando and Vinted, as the income increases, the preference for buyer protection also increases (positive linear correlation).

Last but not the least, age, income, frequency of purchase, buying luxury designer and unique cool clothes have a negative correlation with an additional fee across the reselling platforms.

This means the consumers who fall under these characteristics and motives do not value additional fees as such and might not consider it as an extremely relevant attribute.

1.7 Consumer Segments: Clustering

According to the initially stated research objectives, the study aim is also to identify potential consumers segments and assess who are the potential buyers on second-hand fashion platforms in the current mutated market scenario. To perform such, a cluster analysis will be conducted, based on both perceptual and conjoint analysis data. As in the previous chapters, the following one will include a methodology explanation and a results analysis.

1.7.1 Methodology

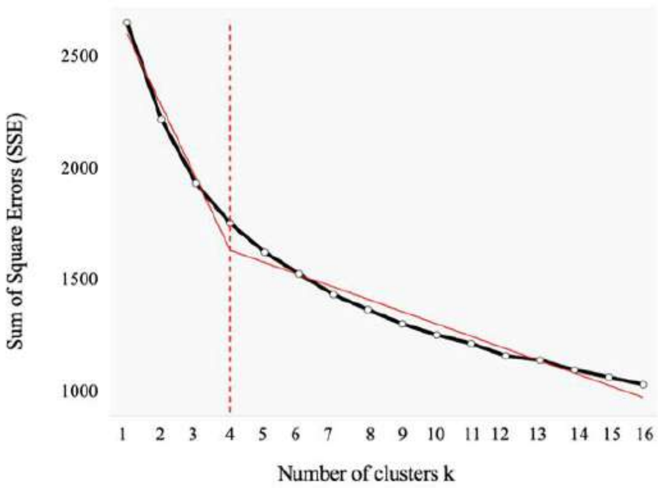
To create a basis to build the clusters on, the two studies conducted before on conjoint and perceptual maps included several behavioural and demographic questions. During the two previous surveys, respondents were asked about their (i) gender, (ii) age, (iii) income level (iv) education level (v) frequency of purchase of second-hand items (vi) motivations for purchasing of second-hand items. Regarding the motivations, consumers had to evaluate 5 macro-motivations: (a) looking for lower prices, (b) looking for good quality items compared to the price paid, (c) finding unique and cool clothing pieces, (d) buying luxury or designers items and (e) sustainability reasons. The survey collection followed the pattern described in the previous surveys methodology (see Chapters 5.1. and 6.1). A total of 228 answers were analysed. This number does not include the number of participants who were excluded due to residency and attention checking.

Some of the variables analysed (i.e. gender, age, income, education, frequency of purchase) were originally expressed in nominal values. In order to use them in the analysis, they were standardised and converted into a numerical ordinal scale. The analyses were then performed using IBM SPSS software and Enginius (a marketing analytics and engineering licensed platform).

1.7.2 Results

At first, an ANOVA was performed over the descriptors. As a result of the analysis (see Table 37, Appendix 11.5), the only variable that resulted not significant was the educational level. Then, the ideal number of clusters was assessed. Generally, clusters number is assessed according to the statistical fit, managerial relevance and targetability. However, when these three elements do not perfectly match, the segments number must be selected using specific marketing techniques. Therefore, we decided to utilise a statistical criterion called the "elbow method", consequently drawing a scree plot. This compared the sum of squared error (SSE) for each cluster solution and measured the within-cluster heterogeneity. A good cluster solution is displayed when the SSE slows dramatically, creating an 'elbow'. When increasing the number of clusters beyond a certain point does not dramatically decrease within-cluster heterogeneity, this means that the clustering should be stopped at that identified point. According to this definition and according to the scree plot results displayed below (see Figure 18), we decided to adopt a 4-clusters solution.

Figure 18: Scree Plot - elbow method

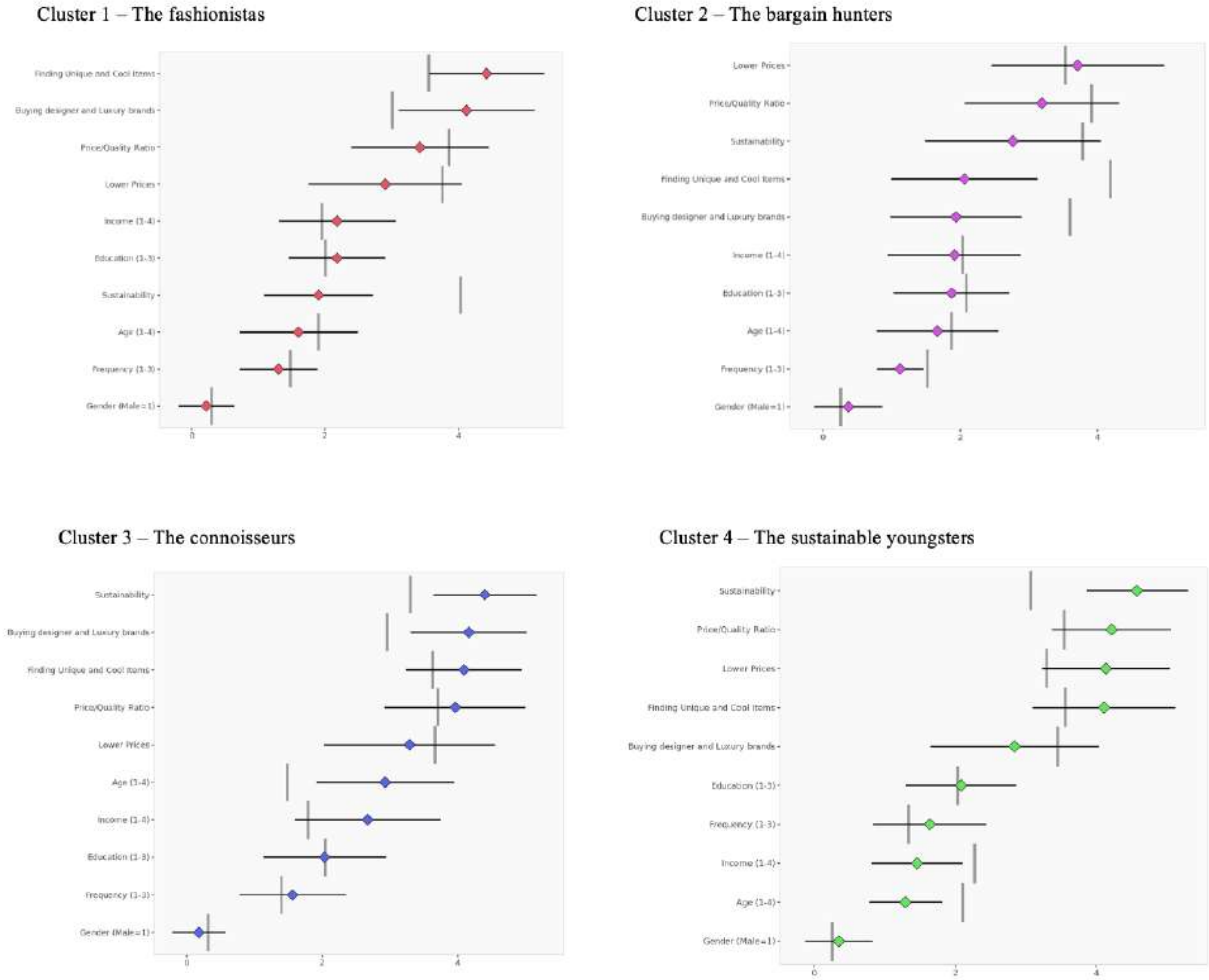


A data aggregation was then performed, generating a new dataset with the centroids for each variable (mean value) related to each segment. For the sake of simplicity and considering the analytical capacities constraints, a k-means clustering analysis was performed. As a result, the sample (N=228) was divided into the following clusters: Cluster 1 with 60 cases, Cluster 2 with 25, Cluster 3 with 72, and Cluster 4 with 71 cases (see Tables 35-36, Appendix 11.5).

Figure 19 represents a visual representation of the segment's descriptive statistics. For each segment, "the segmentation variables are ordered in decreasing order of magnitude and importance. The dots represent the average of the segment. The horizontal lines represent the standard deviations within that segment. The vertical, grey lines represent the averages of the rest of the population, after excluding members of the segment under scrutiny".[9] In order to access the detailed clusters descriptive statistics table, please check Table 38-41, Appendix 11.5.

[9] The graphs description is retrieved from www.enginius.biz. The platform was used to double-check SPSS results and obtain a better data visualisation

Figure 19: Clusters Descriptive Statistics Summary Graphs



<u>Cluster 1: the fashionistas</u>

Cluster 1 is composed of mostly females under 35. These have a monthly income level of 800-1500 euros, an undergraduate educational level and bought less than 3 second-hand fashion items in the last 3 months. This segment mainly purchases second-hand items because they are looking for unique and cool items and luxury and designers clothing. Since this segment is mainly driven by style and brand motivations, we defined it as the fashionistas segment. In order to access the detailed Cluster 1 descriptive statistics table, please check Table 38, Appendix 11.5.

Cluster 2: the bargain hunters

Cluster 2 is composed of both men and women under 35. These have a monthly income level of 800-1500 euros, an average undergraduate educational level and bought less than 3 items of second-hand clothing in the last 3 months. This segment is mostly motivated to purchase second-hand online because of the lower prices. Indeed, they are less interested in finding unique items or designer and luxury clothing, as well as sustainability. In order to access the detailed Cluster 2 descriptive statistics table, please check Table 39, Appendix 11.5.

Cluster 3: the “connoisseurs”

The cluster 3 is made by women over 35+, with an income that is around 1500-2000 euros per month and an undergraduate educational level. They bought between 4 and 6 second-hand fashion items in the last 3 months. They are motivated in buying second-hand fashion because of various reasons: the good quality of the items purchased compared to the price paid, the uniqueness and coolness of the items, the possibility to purchase second-hand designer/luxury brands. As well, they purchase second hand because they care about sustainability. We will define them as “connoisseurs” since they resulted as the cluster with the highest frequency of purchase and drive towards sustainability, items unique and coolness as well as luxury and designer purchase. In order to access the detailed Cluster 3 descriptive statistics table, please check Table 40, Appendix 11.5.

Cluster 4: the sustainable youngsters

The cluster 4 is made by both men and women in their 16-25 with an income that is lower than 800 euros per month and an undergraduate educational level. They bought less than 3 items in the last 3 months. When purchasing second hand, they are motivated mostly by sustainability. Then, they are also driven by the lower prices, the possibility of getting a good quality piece of clothing for the price paid as well as a unique and cool item. This cluster will be called "sustainable youngsters" since it is the cluster containing the youngest individuals who also demonstrated a high drive for sustainability. In order to access the detailed Cluster 4 descriptive statistics table, please check Table 41, Appendix 11.5.

To conclude, it is possible to compare the clustering results with the literature overview and qualitative interviews suggestions. At first, it is noticeable how there is a higher component of females and under 35 years olds among second-hand fashion consumers (Markova and Grajeda 2018). However, the clustering results highlight some segments where the male and 35+ contribution is present and consistent (clusters 2 and 3). The analysis also confirmed that most of the population is made by low-mid income consumers (Markova and Grajeda 2018). Whereas the education level seems to be not significant, with most of the participants having an undergraduate educational level. Additionally, it is possible to state that the majority of consumers purchased less than 3 items in the last 3 months, whereas just a specific cluster (the "connoisseurs") purchased more than 4 items. This is particularly important if we compare the results with the BCG 2020 source, where more than one cluster had a higher frequency of purchase. Moreover, if we compare the motivations results with the literature overview (Hur 2020), we can state that the division between price-conscious, fashion-conscious, brand-conscious and sustainability-conscious is not so neat. Consumers present several motivations across different segments, with peculiar classifications of buyers according to both demographic and behavioural factors. In fact, we can identify a cluster of consumers who is only motivated by price (cluster 2). However, other clusters are both motivated by style and brand (clusters 1 and 3) or just style (cluster 4). Others are also strongly driven by sustainability (clusters 3 and 4).

In the following, in order to validate the clusters and test whether they are able to identify differentiated preferences between different consumer groups, conjoint analysis will be run on each cluster separately and thus will be combining Chapters 6 and 7.

1.8 Cluster-Specific Conjoint Analysis

Following the same approach as in the previous chapters, the next chapter is organized in two parts. The methodology chapter explains the process of the segment-specific conjoint, followed by the results chapter, which sheds light on the differences between the clusters with regards to attribute importance and partworths.

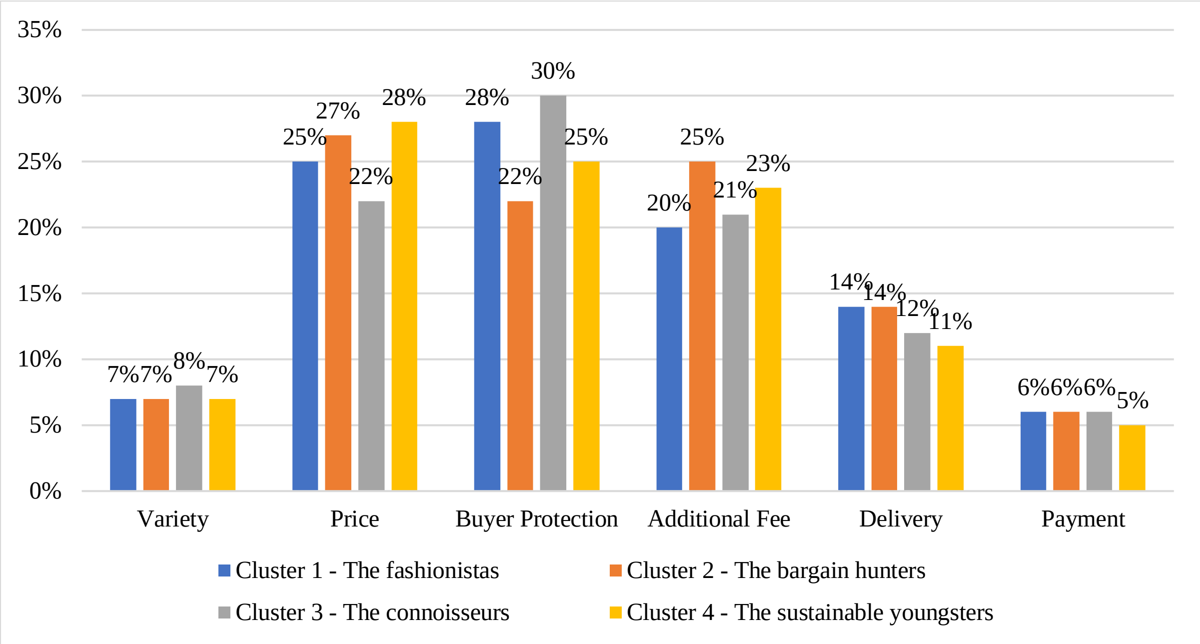
1.8.1 Methodology

For the purpose of the cluster-specific conjoint analysis, the dataset has been filtered according to the clustering criteria. Thus, every respondent has been assigned to one cluster. As a result, sub data sets for each cluster have been built consisting of 32, 15, 24 and 35 respondents for clusters 1, 2, 3 and 4 respectively. In a subsequent step, the importance of the attributes as well as the partworths of the level have been analysed within Excel. To reduce complexity, the average of all four brands per attribute and attribute level has been calculated providing general preferences. Attribute importance and attribute level preference per brand and cluster are yet presented in Appendix 11.6.

1.8.2 Results

The average importance of attributes between the clusters is depicted below in Figure 20. Overall, it becomes evident, that the main variation between the clusters concerns the attributes price, buyer protection and additional fee, which also represent the most important ones given their percentages. Yet, some variation can also be detected within delivery. Payment and Variety importance are more or less on the same level for the individual clusters. In the following, therefore, the analysis will concentrate on price, buyer protection and additional fee.

Figure 20: Average Importance of Attributes between Clusters



Looking at cluster 1, the fashionistas, it is visible, that buyer protection (28%) is slightly more important than product price (25%). The fashionistas assign 20% of importance to the additional fee. Comparing the importance of price to the other clusters, it becomes evident, that the fashionistas care less about it than cluster 2 and 4, but more than cluster 3. The fashionistas are mainly motivated by unique and cool items and finding luxury and designer pieces, which might imply, that price is less important as unique items and luxury goods typically go along with higher prices. As such, the answers to the motivational questions also do reflect the realistic behaviour of the cluster. However, the income is lower than for the connoisseurs for instance, which might explain, why the importance of price is higher as compared to this cluster. For cluster 2, the bargain hunters, price represents the most important attribute (27%), followed by additional fee (25%) and buyer protection (22%). As its name implies, the bargain hunters are mainly motivated by low prices, thus, it seems logical, that they assign high importance to the price. However, this seems to concern both, price and additional fee. In addition, since buyer protection is the least important attribute, the cluster might be more risk seeking.

When taking into consideration cluster 3, the connoisseurs, which is the oldest and wealthiest cluster with the most purchases, the most important attribute with a significant distance to the others is buyer protection (30%), followed by price (22%) and additional fee (21%). This order might on the one hand be justified by an increase of risk aversion with age (Albert and Duffy 2012; Dohmen, et al. 2018). On the other hand, the higher income of the connoisseurs as compared to the other clusters might justify the lower importance of price.

Cluster 4, the sustainable youngsters, puts most importance on the price (28%), followed by buyer protection (25%) and additional fee (23%). The importance of price might be associated with the low monthly income of up to 800€. Interestingly, the sustainable youngsters are less sensitive to the additional fee.

Continuing with the preferences of the levels, the same approach as previously has been followed, and the average values depicted in Table 16 will be analysed.

Table 11: Average Importance of Attribute Levels between Clusters

	The fashionistas	**The bargain hunters**	**The connoisseurs**	**The sustainable youngsters**
Variety				
Offering all types of fashion	2.3%	1.8%	3.8%	3.2%
Offering only one type of fashion	-2.3%	-1.8%	-3.8%	-3.2%
Product Price				
5 €	-1.7%	7.4%	4.1%	10.1%
15 €	0.8%	8.2%	4.8%	7.9%
30 €	6.6%	3.0%	1.8%	-0.5%
50 €	-5.7%	-18.7%	-10.8%	-17.5%
Buyer Protection				
Yes	22,3%	14.1%	20.5%	15.7%
No	-22.3%	-14.1%	-20.5%	-15.7%
Delivery				
Express - 24h	6.6%	5.4%	4.7%	3.8%
Premium - 2-5 working days	-2.5%	-1.4%	-1.1%	-0.3%
Basic - 5-10 working days	-4.1%	-3.9%	-3.7%	-3.4%
Additional Fee				
Free	9.7%	12.6%	11.0%	12.7%
2,99€	3.0%	4.5%	2.2%	3.8%
4,49€	-4.9%	-5.6%	-4.9%	-7.2%

5,99€	-7.8%	-11.5%	-8.4%	-9.3%
Payment				
Basic - CreditCard + PayPal	-1.7%	-0.5%	-1.9%	-1.7%
Advanced - CreditCard + PayPal + Credit from previous sales	1.7%	0.5%	1.9%	1.7%

Taking the fashionistas cluster and its preference for price levels into account, it becomes evident, that the most preferred price is 30€ (6.6%) followed by 15€ with (0.8%). 5€ (-1.7%) and 50€ (-5.7%) represent the least preferred prices. As compared to the others, this cluster has the highest willingness to pay preferring 30€ over all other prices, even rejecting the 5€ priced items. As stated earlier, this could be associated with the cluster's preference for unique items and luxury pieces and their association with higher prices. In addition, the price signalling quality mechanism within this cluster might be stronger than in other ones. Looking at buyer protection, the fashionistas have the strongest preference for the availability of the feature and the strongest aversions against the unavailability with 22.3% and -22.3% respectively. Moving on to the additional fees, the cluster strongly prefers "Free" (9.7%), followed by "2.99€" (3.0%), "4.49€" (-4.9%) and "5.99€" (-7.8%). These results in terms of differences between the levels are comparable to the other clusters.

The bargain hunters have the highest preference for an item price of 15€ (8.2%), followed by 5€ (7.4%), 30€ (3.0%) and 50€ (-18.7%). Despite their motivation for low prices, they prefer the item price of 15€ over the others, which is surprising to some extent. However, they might also be affected by price signalling quality. Comparing the willingness to pay, based on the comparison of the partworths between the price levels between the clusters, it is similar to the connoisseurs, but lower than for the fashionistas and higher than for the sustainable youngsters. With 14.1% and -14.1% for the availability and non-availability of buyer protection, the bargain hunters have the weakest partworth utilities for this attribute. With reference to the additional fee, the same pattern is observable as for the previous cluster with “Free” being the most preferred option (12.6%), followed by “2.99€” (4.5%), “4.49€” (-5.6%) and “5.99€” (-11.5%).

The connoisseurs, who are least interested in prices, also prefer 15€ most (4.8%), followed by 5€ (4.1%), 30€ (1.8%) and 50€ (-10.8€). As such, even if the cluster assigns less importance to the price and has a higher income, it does not have a significantly higher willingness to pay than the others. Its willingness to pay is comparable to the bargain hunters. With 20.5% and -20.5% for the availability and non-availability of buyer protection, the connoisseurs are having the second strongest partworths for the attribute. Also, for the connoisseurs, the pattern within the attribute level preferences for the additional fee does not deviate significantly with “Free” being the most preferred option (11.0%), followed by “2.99€” (2.2%), “4.49€” (-4.9%) and “5.99€” (-8.4%).

The sustainable youngsters, have the lowest willingness to pay preferring 5€ (10.1%), followed by 15€ (7.9%), 30€ (-0.5%) and 50€ (-17.5%). They are the only cluster with a negative preference for 30€. As indicated before, this might be associated with the very low income of the cluster. With 15.7% and -15.7% for the availability and non-availability of buyer protection, the sustainable youngsters are having the second weakest partworths for the attribute after the bargain hunters. Finally, the preference shares for the additional fee following the same order as for the previous cluster with “Free” being the most preferred option (12.7%), followed by “2.99€” (3.8%), “4.49€” (-7.2%) and “5.99€” (-9.3%).

Summarizing the findings of this chapter, it can be said, that there are relatively significant differences between the importance of the three attributes item price, buyer protection and additional fees between the clusters. Taking a closer look at the attribute levels, mainly the item price is differentiating the clusters in terms of their preferences.

1.9 Discussion

1.9.1 Limitations and Further Research Opportunities

The following chapter will discuss the study limitations and based on this, it will provide further research ideas.

Qualitative Interviews and Self-reported data bias. We performed a series of qualitative interviews to gain more detailed insights before structuring the quantitative part. However, self-reported data is limited by the fact that it rarely can be independently verified. Furthermore, whether in interviews, focus groups, or surveys, the accuracy of what individuals say might bring various possible biases in both the interviewer and the interviewee. These biases can be related to consumers' memories and preferences (remembering or not remembering certain experiences or events, preferring one platform over another, etc), but they can also be also business-related (e.g., experts providing insights based on the firm they work for or a limited amount of information they can share with an external interviewer) (Brutus 2013). Nonetheless, qualitative interviews were essential for gathering information about attributes and consumers' preferences, cross-comparing with academic and business research.

Sample sizes. Given the time and financial constraints, sample sizes were kept significantly smaller than suggested, especially for conjoint analysis. Overall, both perceptual maps and conjoint analysis had sample sizes that were greater than n>100 but less than 150. This could have been an issue with regards to statistical significance. Therefore, for future research purpose, we suggest conducting the study on a larger sample population.

Brand Choice Bias. The surveys always included brands as part of the consumers evaluation. Due to this, some platforms might have been favoured compared to others due to their higher brand awareness and recognition. For example, some consumers might have favoured Zalando Second-Hand, even though they never used it.

*Business model comparability***.** The study was conducted considering both B2C and C2C platform models. This created consistent research limitations related to the business models cross-comparison. Indeed, by performing so, the choice of attributes and levels could be more finely tuned to the business model itself. For instance, platforms with different pricing positioning and product strategies have been investigated together, which required a certain degree of simplification. This was done since just few second-hand platforms had a sufficient acknowledgment in the market in order to be tested among consumers. Therefore, future research should investigate either B2C or C2C platforms models separately.

Customers vs. non-customers, buyers vs. sellers. The study focused on both platform consumers and non-consumers. Furthermore, only the buyers' point of view was taken into account, excluding a consistent portion of second-hand platform users, sellers. Therefore, further research should be conducted on this topic, comparing consumers and non-consumers perceptions as well as gathering buyers' insights. Additionally, the buyers - seller distinction might be a further aspect to investigate especially from a clustering and segmentation standpoint (BCG 2020).

Choice of Attributes and Characteristics. Other than the attributes tested in both conjoint analysis and perceptual maps, further characteristics could have been taken into consideration. However, testing more than the chosen attributes could have made the conjoint survey even more challenging for consumers, increasing the abandonment rate or decreasing the attention span. Moreover, due to the complexity of the consumer journey on such a platform, some attributes had to be simplified, such as buyer protection. Therefore, further conjoint analysis studies should be conducted, testing other attributes and assessing further product and service implementations.

Clustering descriptors. The analysis performed contained an assessment of the consumers income level. However, even though the income level is a common way to assess consumers profile, the results revealed that the majority of consumers had a low-mid income level. This might not represent a meaningful insight from a clustering perspective. Indeed, for future research purpose, it would be interesting to investigate consumers' behavior according to the amount spent on the platform for each transaction (BCG 2020).

1.9.2 Findings and Recommendations

The following chapter will summarize the main findings of the study and will give actionable recommendations and market insights to the brand under examination.

<u>How do Italian consumers perceive the different main players and how are those brands positioned in the market?</u>

The findings with regards to consumers' perceptions on the major market players can be summarized as follows.

Vinted is the best positioned platform in terms of Sense of Community, Price Convenience, and Fun and Entertainment. This could be easily justified by comparing the perceptual maps results to some brand inventory[10] and brand exploratory[11] insights. In fact, the overall marketing strategy adopted by Vinted and its users, more price oriented than the rests of competitors, explains why the brand is so well perceived in terms of pricing. Similarly, the platform might highly score on Sense of Community and Fun and Entertainment due to its user interface. In fact, the Vinted presents a more social-oriented purchase experience: users profiles resemble an Instagram page, with "likes" and "follow" buttons, as well as a biography section.

Following on Zalando Second Hand and Vestiaire Collective, it can be stated that they compete in a similar market position. Indeed, they both perform well on attributes such Design and

[10] brand inventory: qualitative analysis of the marketing elements (e.g. price, product, etc) performed through the brand channels (e.g. www.vinted.com)

[11] brand exploratory: qualitative interviews aimed to assess consumer perceptions about the brand (see chapter 4)

Style, Service Quality and Sophistication, Platform Reliability, and Items Quality. These features can be identified as competencies and highlight their expertise in the sector. However, when evaluating both platforms, it is also possible to assert that Vestiaire Collective has a more significant link with these traits because it appears further away from the origin in the vector's direction. This can be justified by comparing these takeaways with some brand inventory and exploratory insights. In fact, Zalando Second Hand was launched just in 2020[12] and the platform might be still associated with its core business, brand-new fashion, as expressed in some preliminary interviews feedback. Indeed, consumers might acknowledge the overall Zalando capabilities in the fashion industry, but they might still perceive Vestiaire Collective as a more knowledgeable competitor.

Finally, regarding Depop, it can be easily noted that the platform underperforms the other competitors on all the elements tested. Based on the perceptual maps analysis, it is possible to conclude that the platform is failing at meeting consumers' needs, or it has a low brand awareness (Keller 2001).

According to what previously stated, it is possible to recommend the following.

1) According to its Sense of community and Fun and Engagement consumers perceptions, Vinted might furtherly leverage this positioning in the market. For example, they might capitalize on these aspects by implementing branded and influencer content creation and onsite users group chats.
2) Due to Zalando close positioning to Vestiaire Collective, it might be possible for the brand to extend part of its second-hand fashion selection into designer and premium second-hand brands, as they did with brand-new fashion. This might be a successful choice due to the higher user base that Zalando can leverage. Similarly, the pre-existing

[12] https://corporate.zalando.com/

relationship with brands can allow second-hand collaborations with brands that need to get rid of unused stock.

3) Since Depop underperformed all the other brands on all fronts, it can be stated that either the brand has a low brand recognition or that its brand performance is declining (Keller 2001). Indeed, the brand should try to invest more in paid advertising in order to attract more and new customers. Similarly, according to the qualitative feedback received during interviews, they should re-scope their delivery and fee strategy in order to attract ex-consumers that abandoned the platform due to price and time convenience reasons.

<u>Which app attributes and brands are most valued by Italian consumers and how can the major market players improve their platform performance?</u>

Moving on to the consumer preferences, taking the overall platform preference into account, Zalando and Vinted turned out to be most preferred platforms followed by Vestiaire Collective and Depop. The main reason for this could be the fact that on average, most of the respondents are looking for fair trades on second-hand platforms and their choices might be also influenced by the pre-existing brand loyalty. Among all attributes, product price, buyer protection, and additional fee were the most preferred attributes across all platforms, which highlights the fact that when in a trade-off scenario, users give importance to these factors the most. There were two types of respondents seen in the survey - the price sensitive and the ones who associate quality with price. Although, most of inclination was towards the 5€ priced products, people were also willing to spend 15€ on Zalando and 30€ on Vestiaire Collective and Depop, which supports the reasoning of some respondents having an association of price with quality. Considering the additional fee, most people preferred paying nothing, but they still showed some willingness to pay for a fee of 2,99€.

As product price also appeared to be one of the significant attributes for consumers, prices with highest preferences in the analysis should be used as a benchmark especially by Zalando Second Hand, Vinted and Depop. However, Vestiaire Collective should further investigate the price preferences of the consumers because it seems unrealistic that luxury fashion will be offered at 30€, and also that the consumers would expect to have luxury items in this price range. In this case, it would have been expected to observe at least the highest preference of 50€ by Vestiaire Collective users.

Creating simulations on price sensitivity, revealed that demand is inelastic for both, product price and additional fee, which was an unexpected finding. Comparing both elasticities for all four brands, it became evident that while for Depop and Zalando the elasticities have been similar, some difference between the two elasticities for Vinted and Vestiaire Collective could be identified. Looking at Vinted, the demand for the additional fee was more elastic than the one for price. For Vestiaire Collective, the opposite has been observed. This shows, that for Vinted, considering price changes, it would be advisable to change the additional fee component, while Vestiaire Collective would be better off changing the product price component. Further, while the drop in item price preferences had been distributed relatively evenly with an incremental price increase from one price level to another, for the additional fee, a more significant drop was observed from “Free” to “2,99€”, especially for Zalando. Therefore, it is not recommended for Zalando to change the additional fee.

Buyer protection was another one of the most important attributes especially in the case of C2C platforms such as Vinted and Depop as compared to B2C platforms, maybe since being confronted with fraud is more likely on a consumer-to-consumer platform. Due to the importance of buyer protection and the fact, that the attribute is more complex than presented in the study, as there are multiple ways to improve trust on a platform, e.g. through reviews in the case of

C2C platforms, we would recommend the platforms to further investigate this attribute and how it can be setup in a way, its most efficient.

Compared to the three top-attributes, delivery services, type of variety on the platform and payment options were given the least attention by the respondents when making a close to real-life market choice. Regarding the delivery services, there could be possibility that respondents might not have associated the delivery services as part of the platform attributes but rather as a third-party service. Although the preference for variety and payment options was not the highest, but consumers have shown preference for having all types of variety and credit wallet on these reselling platforms. These findings can be insightful for the platforms to incorporate these features, if they do not have it already.

Moreover, it was identified in the correlation among the variables and highest ranked attributes that consumers from the upper age group do not give much importance to product price. Also, when people have a high frequency of purchase from second-hand platforms or are looking for unique or branded clothes, they tend to have buyer protection as part of their trade. On the contrast, people who have high frequency of purchase, buy second-hand luxury and unique items and are also from upper age and income bracket, do not find additional fee as an extremely relevant attribute.

What are the relevant consumer segments purchasing on second-hand platforms?

According to the k-means clustering conducted, the ex-post segmentation revealed 4 possible clusters.

The first one, the fashionistas, are women under 35, with an undergraduate educational level and an 800-1500 monthly income. They bought less than three second-hand fashion items in the last three months, and they mainly buy second-hand fashion products because of their uniqueness and coolness, as well as premium and designer attire.

The second cluster is made by bargain hunters. They are men and women under 35 with an undergraduate educational level, earn between 800 and 1500 euros a month, and bought less than 3 second-hand clothing items in the last 3 months. This group buys second-hand fashion online mainly to save money. They have no interest in coolness and uniqueness, designer and luxury apparel, or sustainability.

The third cluster is made by the connoisseurs: over-35-years-old women with a monthly salary of 1500-2000 euros and undergraduate educational level. They bought between 4–6 second-hand apparel items in the last 3 months. Affordability, uniqueness, and coolness of are all motivating factors for them as well as acquiring designer/luxury brands. They also buy second-hand to help the environment. Overall, they are the cluster with the highest frequency of purchase and income. Similarly, they have a stronger motivation for sustainability, uniqueness and uniqueness, as well as luxury and designers.

The last cluster is the one made by sustainable youngsters. It's composed of men and women aged 16-25, having a monthly income of less than 800 euros and an undergraduate educational level. They bought less than 3 items in the last three months and are mainly driven environmental and pricing concerns when purchasing second-hand apparel. In this cluster, we can find the youngest people with a strong motivation towards sustainability.

Overall, when comparing to the literature overview (Hurr 2020) to the study discoveries, the price-conscious, fashion-conscious, brand-conscious, and sustainability-conscious categories are not so clearly defined and divided, with a higher diversification of consumers motivations. Additionally, based on the findings, we would generally recommend removing the educational and income level as population descriptors. In fact, two clusters out of four had a middle income, while all the clusters analysed had an undergraduate educational level. Variables that might be tested instead are: the average amount spent on the platform per transaction (giving more direct and actionable insights about the segment profitability), the distinction between buyers and sellers and having or not children (as emerged during some qualitative interviews and as tested by BCG 2020).

<u>How do consumers preferences differ across market segments?</u>

Applying the identified clusters on the conjoint analysis, the results per cluster are the following.

The fashionistas with a preferred item price of 30€ have the highest willingness to pay, a high need for buyer protection and see the additional fee as a relatively unimportant feature. The bargain hunters, motivated by low prices, have a relatively low willingness to pay with a preferred price of 15€. Moreover, buyer protection plays a subordinate role, while additional fee is relatively important. The willingness to pay for the connoisseurs, who have multiple motivations and purchase more frequently than the other clusters, is comparable to the bargain hunters with 15€ as preferred item price. Yet, the item price, as well as the additional fee are rather unimportant. This cluster has the highest need for buyer protection. The sustainable youngsters, with a preferred item price of 5€ have the lowest willingness to pay, a relatively low need for buyer protection and consider the additional fee as relatively important. Due to the fact, that clear differences of needs between the clusters, at least in some of the attribute and attribute level preferences could be identified, it can be said that the clusters provide a meaningful way of segmentation, which can in turn be used for targeting. Therefore, in the following, it is possible to make some recommendations for the platforms in this context.

Overall, the segmentation results, together with the conjoint analysis and perceptual map insights can allow us to make some possible targeting discussion.

From a motivational perspective, Vestiaire Collective best matching target groups would be the fashionistas and the connoisseurs. Indeed, buying designer-luxury as well as cool and unique items are the main drivers for both consumer segments. Additionally, the connoisseurs have the highest income level and frequency of purchase across the different segments. This makes them a particularly profitable segment and a good match for Vestiaire Collective. Similarly, in terms of positioning, Vestiaira Collective seems to be the platform with the most positive associations with quality aspects, as well as a more premium-pricing when compared to Vinted and Zalando. However, despite what mentioned, none of the clusters resulted in a willingness to spend more than 30€ per item during the conjoint-specific conjoint analysis. This is especially valid for the connoisseurs, as despite their high income, they have a lower willingness to pay than the fashionistas. Therefore, it is questionable whether this type of targeting is effectively impactful in a real-life scenario.

Due to the negative results obtained in the perceptual maps analysis, it is difficult to state how Depop precisely can match any of the consumers' segments examined in the paper. However, in a better market scenario (higher brand awareness and recognition), it would be recommendable to target the fashionistas due to their willingness to pay and their motivation to find unique and luxury items.

Finally, due to the lower willingness to pay of bargain hunters and sustainable youngsters, Vinted and Zalando seem to be a better match with these clusters. The pricing is also confirmed by the perceptual maps results. Additionally, since these two mentioned clusters have a comparatively low need for buyer protection, they better match with the offer of Vinted, which offers buyer protection but also allows purchases without it, resulting in lower costs.

2 Individual Part

2.1 Introduction

The analysis of partworth utilities in chapter 1.6.2 among others allowed us to find out, that the most important attributes to the consumers have been buyer protection, product price and additional fee. Therefore, we created counterfactual scenarios based on these three attributes with the aim to further investigate consumer preferences in the scope of the composition of the attributes that is currently available in the market. For instance, taking into account the most realistic market scenarios, it was also possible to identify the most popular platform in the market. Yet, this analysis also allowed us to compare the price sensitivity between the different pricing components.

2.2 Conjoint Simulations

We took the estimates from conjoint analysis to simulate counterfactual market scenarios. As such, we gathered additional insights on price elasticity of demand for product price and additional fees as well as on buyer protection since these three attributes have been identified as the most important in the previous part. As a first step, the baseline scenario has been defined representing the most realistic combinations in the market, as described in the following.

Regarding Variety, all platforms except for Vestiaire Collective offer a rather broad set of apparel categories. Even if Depop has a focus on vintage, the platform also offers clothes from other fashion categories, therefore, it seemed justified to choose "offers all types of fashion". For the price positioning, based on the impression on the market also confirmed by the interviews, Vestiaire Collective sells for the highest prices, followed by Depop and Zalando which were both assigned 30€ and Vinted, which was clearly seen as the platform with the lowest prices and thus assigned to 5€.

For the buyer protection, all the platforms do provide some kind of buyer protection mechanism in the case of fraud or delivery of faulty items. As the delivery time mainly depends on the carrier and on the seller, it has been assumed that on average, it takes 5-10 days from the moment of purchase to the arrival at the buyer's location. Also, the additional fees have been assigned to meet the most realistic market conditions. Zalando offers free delivery from a purchase value of 24.90€.[13] Since a price of 30€ has been assumed for Zalando, the option "Free" was chosen for the platform. As described in Chapter 1.2.3 and 1.6.1, Vinted charges 0.70€ plus 5% of the purchase price as buyer protection.

In reality, the shipping costs for Vinted, Depop and Vestiaire Collective will depend on the carrier, the package size, the distance and the fee the seller will charge for the shipping. For Vinted, there are some sellers not charging any shipping costs, but most likely include them in the product price. However, the platform claims that the shipping costs have to be paid by the buyer.14 As a result, for all platforms, shipping fees of around 5€ have been assumed based on some trials on packlink.com within the Italian market, and suggestions on what to charge from the platforms themselves.15 Packlink is a shipping fee and service comparison platform, where it is possible to include the distance covered and the package size.16 As Vinted charges buyer protection extra, 5.99 € has been assumed as most realistic scenario for additional fees. For Depop and Vestiaire, the option "4.49€" has been chosen. Moreover, Vinted as described in chapter 1.2.3 provides the consumer with an in-app feature allowing to pay with credit from previous sales, while the other platforms do not. As a result, the baseline scenario is composed of the combinations in Table 11.

Table 12: Configuration of Baseline Scenario

[13] https://www.zalando.it; https://faq.vestiairecollective.com
[14] https://www.vinted.it
[15] https://depophelp.zendesk.com; https://faq.vestiairecollective.com/
[16] https://www.packlink.com/en-GB/

	Zalando Second-Hand	Vinted	Depop	Vestiaire Collective
Variety	Offers all types of fashion	Offers all types of fashion	Offers all types of fashion	Offers only one type of fashion
Product Price	30€	5€	30€	50€
Buyer protection	Platform offers the guarantee	Platform offers the guarantee	Platform offers the guarantee	Platform offers the guarantee
Delivery Service	Basic delivery in 5-10 working days	Basic delivery in 5-10 working days	Premium delivery in 5-10 working days	Basic delivery in 5-10 working days
Additional fee / purchase	Free	5.99€	4.49€	4.49€
Payment options	Basic: CreditCard + PayPal	Advanced: CreditCard + PayPal + Credit from your previous sales	Basic: CreditCard + PayPal	Basic: CreditCard + PayPal

Preference Shares of the Baseline Scenario

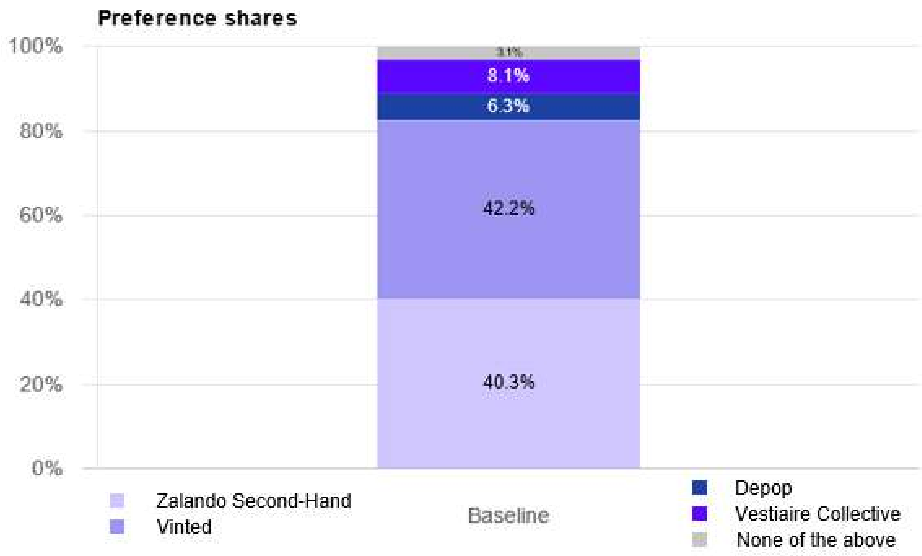
Based on the scenario provided, as seen below in Figure 16, the preference shares for the combinations provided in Table 11 above are given. In this scenario, the most preferred platform is Vinted with 42.2% followed by Zalando Second-Hand with 40.3%, Vestiaire Collective with 8.1%, Depop with 6.3% and none of the above with 3.1%.

Preference shares can be interpreted as an approximation of market shares, however, failing to take into account some real-market factors such as shelf-space or frequency of purchase that might differ from product to product. Also, the simulator fails to take into account "share for mind", which implies that in the simulation, the period for which a product has been in the market does not play a role. However, newer products will typically have fewer habitual consumers and less awareness of the product. This could be the case for Zalando Second Hand, which has only been introduced in 2021 to the Italian market.[17] It can therefore be assumed,

[17] https://corporate.zalando.com/en/newsroom/

that our analysis inflates the importance of Zalando Second Hand, also because most consumers probably associate the "regular" Zalando online shop with the brand.

Figure 16: Preference Shares Baseline Scenario



Comparing the results of the baseline scenario with the assumption of market shares / importance in the market based on the interviews, it can be assumed that Zalando plays a way less important role than depicted here. Consumers have rarely mentioned Zalando for their second-hand purchases in the preliminary interviews. However, the high preference for Zalando could be an indicator for the strong and widely known brand of the company overall (not necessarily connected to Zalando Second Hand) and thus a confirmation for the sophistication of the step to enter the online second-hand market from a demand-side perspective.

<u>Demand Elasticities</u>

In order to retrieve the price elasticity of demand and the preference shares for different price levels, four scenarios have been developed, one for each brand taking the baseline scenario into account. Here, besides the baseline scenario price, also the other three prices for each brand have been displayed to see the impact of the price changes on the preference shares. The four scenarios are depicted in Figures 30 to 33 in Appendix 4.4.2.3 as graphs showing not only the impact of the price change of the respective brand on its own preference share, but also on the preference shares of the other brands. Table 12 represents a summary including solely the preference shares for the brand whose price has been changed as well as the average price elasticity of demand per brand.

The calculation of the price elasticity of demand is based on the arc elasticity formula, which is more useful when considering price ranges (Pindyck and Rubinfeld 2018). The elasticities depicted in Table 12 represent the averages of each elasticity from one price point to the other. It becomes evident, that price elasticity of demand for each brand is inelastic. As such, a 1% increase in price leads to a less than 1% decrease in demand (Pindyck and Rubinfeld 2018, 55). Price elasticity of demand can be influenced by the availability of alternatives, but also by brand loyalty or the association of a higher quality with a higher price (Krishnamurthi and Raj 1991; Pindyck and Rubinfeld 2018). However, for online second-hand platforms, we expected to see an elastic demand. For Depop, price elasticity of demand is -0.9, followed by Vinted with -0.6, Zalando Second Hand with -0.4 and finally Vestiaire Collective with -0.1. In the table, all lines have to be understood individually from each other, and only comparisons of prices within each line are meaningful.

Table 13: Product Price Variation - Preference Shares and Price Elasticity of Demand

Scenarios per Brand	**5 €**	**15 €**	**30 €**	**50 €**	**Average PED**
Zalando	51.3%	60.4%	40.3%	26.6%	-0.4
Vinted	42.2%	37.8%	25.2%	16.9%	-0.6
Depop	8.6%	5.6%	6.3%	2%	-0.9
Vestiaire Collective	9%	5%	12.7%	8.1%	-0.1

These results might be caused by the reasons described above. As such, consumers for Depop react more strongly to price changes than for Vestiaire Collective. For Depop and Zalando having a rather higher price level, the argument price signalling quality might apply, while brand loyalty might also play a role. However, the difference between the two platforms might be explained by the fact, that Depop is the smaller player and less known as compared to Zalando which could cause lower brand loyalty. For Vinted, price signalling quality could also play a role, however, probably to a lesser extent, as the price level on the platform is lower. Yet, it is possible, that with Vinted as the market leader, there is a certain degree of brand loyalty, but also a perceived lack of alternatives for the consumers, which could explain the low price elasticity. With regards to Vestiaire Collective, it is interesting to see that the PED is still negative, but least negative among the brands. This might again be explained by price signalling quality, which could especially apply to Vestiaire Collective with its focus on luxury fashion and the in this context often mentioned snob effect (Pindyck and Rubinfeld 2018, 155).

Besides the reasons provided above, one must consider that the inelastic demand might be caused by methodological reasons as already considered previously. On the one hand, the decision-making scenario aimed to be as realistic as possible, but still, the respondents did not have to make a decision when filling out the survey. This might have made them less attentive to price. On the other hand, the sample is relatively small, reducing the statistical significance of the survey results.

Based on the results taking the inelastic demand into account, the platforms seem to have more leeway in pricing than expected. For the lowest pricing competitor in the market, it could be advisable to increase prices, which would be Vinted in our case. However, since the platform does not intervene in the pricing of its sellers, it would not do this. Vinted does not charge any fee related to the product prices and thus does not generate its revenue through product prices. Therefore, it would only be impacted negatively by the drop of demand if it tried to impact the pricing. For the other platforms, a price increase would not be advisable, as the consumers might then move to the cheapest competitor given they have a comparable offer.

For Zalando Second Hand, the ideal price seems to be 15€, resulting in a preference share of 60.4%. For Vinted, the ideal price would be 5€, resulting in a preference share of 42.2%. For Depop, the ideal price is also at 5€, which is assumed to be further away from the market situation than for Vinted resulting in a 8.6% preference share. For Vestiaire Collective, the ideal price is 30€, significantly exceeding the ideal price levels of Vinted and Depop with a preference share of 12.7%.

So far, we have only compared isolated simulations, such that each company is unable to match the price changes of the others. We now investigate the case where all companies optimize their prices according to the analysis above, in order to provide an idea of competitive effects. The impact on the preference shares as compared to the Baseline scenario is depicted in Figure 17.

Figure 17: Product Price Variation - Preference Shares and Price Elasticity of Demand

Enacting these changes, it becomes clear, that as compared to the ideal price scenarios where only one platform changes their prices at a time, Vestiaire Collective is the winner. As visible through the comparison with Table 12 instead of 12.7% preference share, the company reaches 14.2%. While Zalando Second Hand only registers a slight loss from 60.4% to 58.5%, Depop and Vinted are significantly worse off as compared to the other scenario with a drop from 42.2% to 21.0% for Vinted and 8.6% to 4.0% for Depop. It must be considered here that the price for Vinted already was at 5€ in the baseline scenario and all other prices have been lowered, which makes it natural, that Vinted faces a significant drop in preference share.

Since the additional fee attribute has been among the top 3 most important attributes across all brands and represents a potential revenue source for the platforms on the consumer side, in the following, an analysis of the price elasticity of demand on additional fees has been conducted. Analogous to the previous analysis, the baseline scenario was taken as a foundation for the analysis and all factors have been unchanged except for the additional fees in the different scenarios. The calculation of the price elasticity has been conducted in the same way as for the product price. As visible in Table 13 below, for all the brands, the price elasticity is very low as well, against the expectations. Depop has the highest elasticity with -0.9, followed by Vestiaire Collective with -0.6, Zalando with -0.4 and Vinted with -0.2. Since additional fees did represent a mixture of buyer protection and delivery fees, there might be some additional value associated with higher fees and to a certain extent price signalling quality could apply here as well. Interestingly, for Vinted, which transparently communicates the amount of buyer protection fees on the product pages, the elasticity of demand is very low, which could strengthen the explanation of price signalling quality outlined before. In addition, as described in chapter 1.3.5 transparency on fees can positively impact consumer engagement on online marketplaces, this might be an explanation for an increased level of brand loyalty on Vinted resulting in a higher price elasticity of demand, i.e., a very inelastic demand.

Table 14: Additional Fee Variation - Preference Shares and Price Elasticity of Demand

Scenarios per Brand	**Free**	**2.99 €**	**4.49 €**	**5.99 €**	**Average Price elasticity of demand**
Zalando	40.3%	22.2%	19.6%	18.1%	-0.5
Vinted	60.2%	53.8%	38.8%	42.2%	-0.2
Depop	18.5%	14.9%	6.3%	4.4%	-0.9
Vestiaire Collective	10.6%	13.3%	8.1%	4.3%	-0.6

As visible above, the attribute level "Free" is the most preferred one for Zalando, Vinted and Depop. However, for Vestiaire Collective, with "2,99€" as most preferred option, the respondents seem to be willing to pay a little more.

Looking at the "slope" of the changes in preferences for the different fee levels, it can be observed, that it reduces. The change from charging nothing to 2,99€ is significantly stronger than from 2,99€ to 5,99€, which represent the same distance in euros. This implies, that changing the fees from "Free" to 2,99€ would result in a significant drop in preference, which is particularly relevant for Zalando. The fact that the platform typically delivers the items for free might serve as explanation for the drastic decline in preference from 40.3% for "Free" to 22.2% for "2.99€". The underlying psychological concept might be prospect theory, which implies that a loss of something that has already been achieved or owned will result in a significant loss in satisfaction (Kahneman and Tversky 1979). Therefore, especially for Zalando, it might be more difficult to implement changes on the fees than for the other platforms.

Having added both the product price and the additional fee also allows another comparison: How sensitive are consumers to a change in the additional fee as compared to a change in the product price?

Table 15: Comparison of Product Price and Additional Fee Elasticity

Brand	**Price Elasticity of Demand – Product Price**	**Price Elasticity of Demand – Additional Fee**
Zalando	-0.4	-0.5
Vinted	-0.6	-0.2
Depop	-0.9	-0.9
Vestiaire Collective	-0.1	-0.6

Looking at Table 14, we find that consumers do not all think of expenditures via price and fees as equivalent. For Zalando Second Hand and Depop, the sensitivity to a change in either product price or additional fee is comparable. However, the cases of Vinted and Vestiaire Collective are remarkable. For Vinted, the price elasticity for the product price exceeds the one of the additional fee and for Vestiaire Collective, we observe the opposite direction. These results may depend on individual-company factors, such as positioning and platform design. In practical terms, if these companies are to employ price increases, then Vinted would be better off doing so via fees, while Vestiaire Collective may be better off increasing product prices directly.

For a more detailed depiction of the different scenarios on different additional fees for all four brands, see Figures 34 to 37 in Appendix 11.4.2.3.

Analogous to the approach for item price and additional fee, also scenarios for both buyer protection options have been developed. Looking at the impact of the buyer protection attribute on preference shares depicted in Table 15, it is clearly visible, that is has a strong impact, which due to the attribute's importance as analysed before is not surprising.

Table 16: Impact on buyer protection on preference shares

Preference shares	**Buyer protection is available**	**Buyer protection is not available**	**Change in %**
Zalando	40.30%	8.20%	-79.7%
Vinted	42.20%	15.40%	-63.5%
Depop	14.90%	6.50%	-56.4%
Vestiaire Collective	8.10%	1.70%	-79.0%

For all brands, some kind of buyer protection is indispensable resulting in an at least 56.4% drop of preferences in our sample if it is not available. Interestingly, for Zalando and Vestiaire Collective, buyer protection seems to be even more important relatively than for Vinted and Depop. The sharp decline in preference shares for the B2C platforms might again be explained by prospect theory and loss aversion. Especially for Zalando, buyer protection is a matter of course since the company accepts all kinds of returns as opposed to the other platforms. As a consequence, the loss of the feature results in a drastic decline of preference.

Please see a detailed overview of the impact of buyer protection on the preference shares of the brands in Figures 38 to 41 in 11.4.2.3.

2.3 Conclusion

In summary, we observed that given the most realistic market scenarios, Vinted is the most popular platform followed by Zalando Second-Hand, Vestiaire Collective and Depop. The high preference share for Zalando, despite its assumed low market share, might be a proof of success of the strategic decision of the company to enter the second-hand market.

Taking a closer look at price elasticity of demand, the results were surprising. Instead of facing an elastic demand as expected for this kind of service, the demand was inelastic for both price components and all brands. This demonstrates that the platforms might have more leeway in pricing that expected. These results might arise from brand loyalty, a lack of alternatives or price signalling quality. However, it is also likely, that methodological reasons play a role such as the small sample size and the fact that the decision making was simulated.

Based on the comparison of price elasticity between the components within the brands, it became clear that due to the significant differences, for Vinted it would be advisable to enact price increases on the additional fee, while for Vestiaire Collective it would be advisable to increase the product price.

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4 Appendix

4.1 Relevant Reselling Apps in the Italian Market

Figure 21: Screenshot Similarweb.com - Top Apps in Italy Category "Shopping"

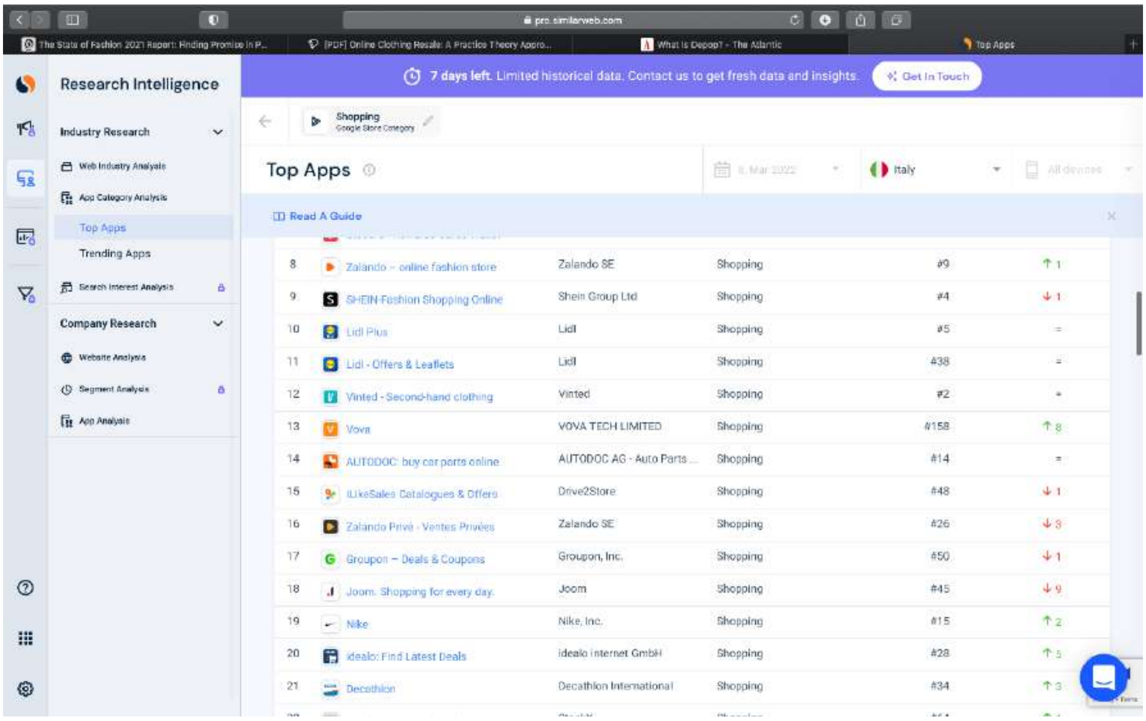
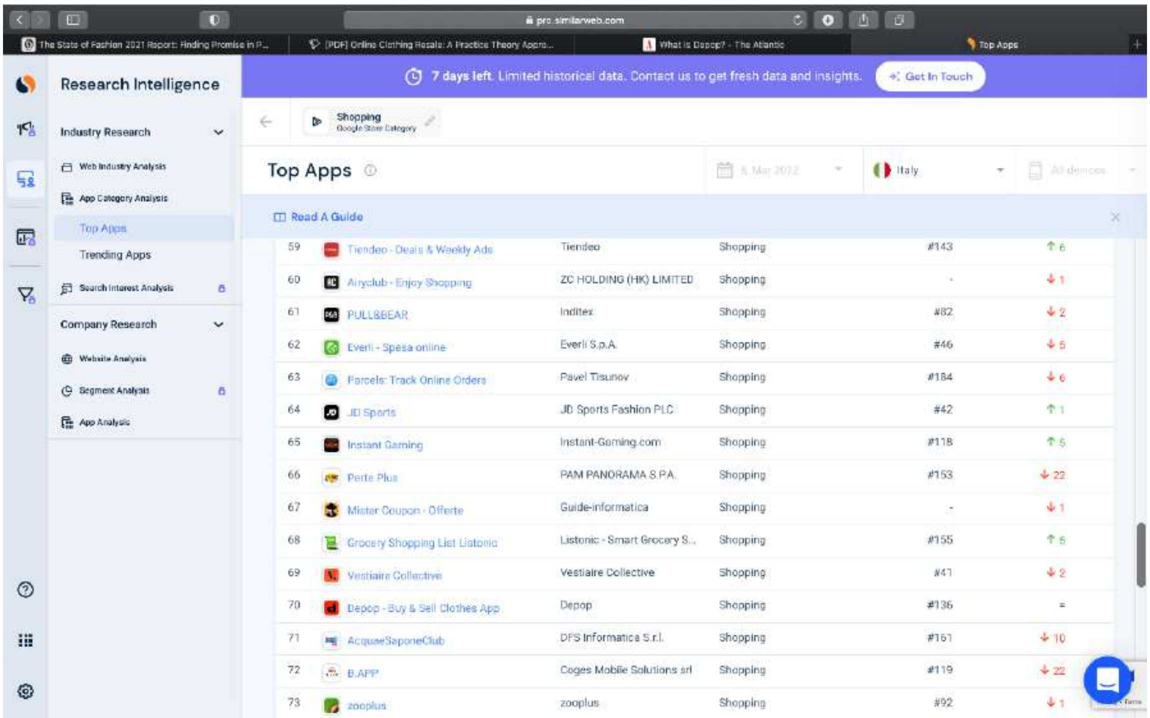


Figure 22: Screenshot Similarweb.com - Top Apps in Italy Category "Shopping"



4.2 Preliminary Interviews

4.2.1 Questions

Table 17: Interview Questions – Professionals

Professional experience	- Years of experience - Current Role
Age, Gender, Income, Frequency of Purchase, Education level	- Do you think that these descriptors are pertinent and useful in describing the consumers?
Motivations	- What are the main reasons why consumers purchase on second-hand platforms?
Attributes	- According to your experience on the topic and in the field, what do you consider the most important attribute that users evaluate when using second-hand platforms?
Preferences	- According to you, what is the top-ranked attribute, determining the choice between one platform and another?
Market Perceptions	- According to you experience, how do consumers perceive the following second-hand apps (Vinted, Depop, Vestiaire Collective, Zalando Second Hand)?
Additional Value and Future Prospective	- Do you think that studying such characteristics will bring additional value to the research on this topic?

Table 18: Interview Questions - Users

Demographics	- Age - Gender - Education - Frequency of Purchase
Usage experience	- Have you ever purchased on a second- hand platform? - Which platforms do you know?

	- Which ones do you use? - How long have you been knowing and using these platforms?
Motivations	- What are the main reasons why you purchase on these platforms?
Attributes	- Now, let’s focus on the experience with your favourite app. Could you please describe it in detail? - What characteristics you value the most? - Is there any feature that you would like to be added to these apps?
Market Perceptions and Preferences	- Are you able to identify differences between the different platforms previously mentioned? - Why you use certain platforms and not others?

4.3 Perceptual Maps

4.3.1 Survey Setup

Table 19: Questionnaire Perceptual Maps - English version

<table>
<tr><td colspan="8">Questionnaire on second-hand clothing platforms
Hi there! We are a group of 5 female university students. We are currently doing a dissertation on second-hand clothing apps (Vinted, De-pop, Vestiaire Collective, Zalando Second Hand).
Our goal is to understand the opinions and perceptions of consumers about these apps.

Completion time: 5 minutes.

By giving us your opinion, you would be making a great contribution to research in this area and helping us to complete our thesis :)
Important: The information you share will remain anonymous and will be used for research purposes only.
In this section, we will ask you to evaluate the platforms based on the criteria mentioned below. Please note: you must complete each question to be able to finish the questionnaire.</td></tr>
<tr><td>Sections</td><td>Description</td><td>Question</td><td>Consideration features</td><td colspan="4">Answer</td></tr>
<tr><td>Section 1</td><td>Determine whether the <u>participant corresponds</u> to our study</td><td>1. Have you been living in Italy in the last 5 years?</td><td>Not applicable</td><td colspan="4">1. Yes
2. No (End of survey)</td></tr>
<tr><td rowspan="7">Section 2</td><td rowspan="7">Assess the <u>perception</u> of the different services provided by each platform.</td><td rowspan="2">2.Price Convinience</td><td rowspan="2">- Items price
- Commission and purchase fees
- Delivery fees</td><td>Depop</td><td>Vestiaire Collective</td><td>Vinted</td><td>Zalando Second Hand</td></tr>
<tr><td colspan="4">Rate on a scale of 1 to 5 where
1=Very Dissatisfied and 5=Very Dissatisfied</td></tr>
<tr><td rowspan="2">3. Items Quality</td><td rowspan="2">- The items overall quality and conditions
- The level of hygiene</td><td>Depop</td><td>Vestiaire Collective</td><td>Vinted</td><td>Zalando Second Hand</td></tr>
<tr><td colspan="4">Rate on a scale of 1 to 5 where
1=Very Dissatisfied and 5=Very Dissatisfied</td></tr>
<tr><td rowspan="2">4. Reliability</td><td rowspan="2">- Certainty of receiving the item ordered
- Delivery tracking
- Website product being the same as the item received</td><td>Depop</td><td>Vestiaire Collective</td><td>Vinted</td><td>Zalando Second Hand</td></tr>
<tr><td colspan="4">Rate on a scale of 1 to 5 where
1=Very Dissatisfied and 5=Very Dissatisfied</td></tr>
<tr><td>5.Design and Style</td><td>- Pictures quality
- Website navigability</td><td>Depop</td><td>Vestiaire Collective</td><td>Vinted</td><td>Zalando Second Hand</td></tr>
</table>

			- Overall platform aesthetic appeal	Rate on a scale of 1 to 5 where **1=Unsatisfactory and 5=Excellent**
		6. Fun and Entertainment	- The platform's ability to surprise you with new item discoveries - Enjoyment and hunting trill	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Rate on a scale of 1 to 5 where **1=Very Dissatisfied and 5=Very Dissatisfied**
		7.Service Quality and Sophistication	- Offering a basic/standard service versus a more sophisticated and upper-level service	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Rate on a scale of 1 to 5 where **1=Unsatisfactory and 5=Excellent**
		8.Sense of Community	- Sense of community and place attachment - Possibility of weaving and nuturing relationships on the platform	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Rate on a scale of 1 to 5 where **1=Very Dissatisfied and 5=Very Dissatisfied**
Section 3	Analyze the **<u>demographic</u>** features of the collected sample	9. What is your gender?	**Not applicable**	1.Female 2. Male
		10. Whats is your age?	**Not applicable**	1. 16-25 years old 2. 26-35 years od 3. 36-45 years old 4. 46+ years old
		11. What is the highest level of education you have completed?	**Not applicable**	1. Less than/equal to a High School Diploma 2. Bachelor's degree 3. Master's degree 4. MBA/PhD
		12. What is your average montly income?	**Not applicable**	Less than 800 Between 800 and 1,500 Between 1,500 and 2,000 Between 2,000 and 3,000 More than 3,000
	Determine the **frequency distribution** of the collected sample in the industry	13. In the last three months, how many items ofsecond hand clothes did you buy?	**Not applicable**	1. 1-3 2. 4-6 3. More than 7
	Assess the **motivations** of the users that drive them to purchase second-hand fashion online	14. Evaluate the following reasons why you purchase second-hand fashion online	**Not applicable**	Lower Prices | Price/Quality Ratio | Finding Unique Items | Buying Designer and Luxury brands Evaluate the given reasons on a scale of 1-5. **1=Little Influential, 5=Very Influential in my choice**

Table 20: Questionnaire Perceptual Maps - Italian version

Questionario sulle piattaforme di abbigliamento di seconda mano

Ciao! Siamo un gruppo di 5 studentesse universitarie. Al momento stiamo realizzando una tesi di laurea sulle app di abbigliamento di seconda mano (Vinted, Depop, Vestiaire Collective, Zalando Second Hand).
Il nostro obiettivo è capire quali sono le opinioni e percezioni dei consumatori su queste app.

Tempo di completamento: 5 minuti.
Dandoci il tuo parere, daresti un grande contributo alla ricerca in questo settore e ci aiuteresti a completare la nostra tesi :)

Importante: le informazioni che condividerai rimarranno anonime e verranno utilizzate ai soli fini di ricerca. In questa sezione ti chiederemo di valutare le piattaforme sulla base dei criteri menzionati di seguito. Attenzione: devi completare ogni quesito per poter terminare il questionario.

1. Hai vissuto in Italia negli ultimi cinque anni?		1. Si 2. No
2.Price Convinience	Tieni in considerazione: () prezzo degli articoli sulla piattaforma () commissioni sugli acquisti costi di spedizione	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Poco Conveniente e 5=Molto Conveniente**
3. Qualità dei Prodotti	Tieni in considerazione: () la qualità e le condizioni generali degli articoli () livello di igiene dei capi	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Bassa Qualità e 5=Alta Qualità**
4. Affidabilità della Piattaforma	Tieni in considerazione: () la certezza di ricevere l'articolo ordinato () la tracciabilità della consegna corrispondenza tra il prodotto	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1= Poco Affidabile e 5=Molto Affidabile**

	ricevuto e l'immagine del prodotto sulla piattaforma	
5. Design e Stile della Piattaforma	Tieni in considerazione: () la qualità delle foto () la navigabilità del sito () estetica e bellezza generale della piattaforma	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Insoddisfacente e 5=Eccellente**
6. Divertimento e Intrattenimento sulla Piattaforma	Inteso come: () l'abilità della piattaforma di stupirti con capi che sono una nuova e felice scoperta () divertimento nella ricerca di nuovi capi	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Poco e 5=Molto**
7. Qualità del servizio	Inteso come capacità della piattaforma di offrire servizi base oppure un servizio più sofisticato e su misura per te.	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Standard e 5=Elaborato**
8. Senso di appartenenza alla comunità	Inteso come: () sentirsi parte della community della piattaforma () capacità di interagire e coltivare relazioni con rivenditori e altri utenti	Depop | Vestiaire Collective | Vinted | Zalando Second Hand Valuta su una scala da 1 a 5 dove **1=Poco e 5=Molto**
9. Qual è il tuo sesso?		1. Donna 2. Uomo
10. Qual è la tua età?		1. 16-25 anni 2. 26-35 anni 3. 36-45 anni 4. 46+ anni
11. Qual è il tuo livello di istruzione?		1. Scuola Secondaria (e.g. medie, liceo) 2. Istruzione Universitaria 3. Istruzione post-universitaria
12. Qual è il tuo reddito medio mensile?		1. Meno di 800 2. Tra 800 e 1,500 3. Tra 1,500 e 2000 4. Tra 2,000 e 3,000 5. Più di 3,000
13. In the last three months, how many items of second hand clothes did you buy?		1. Meno di 3 capi 2. Dai 4 ai 6 capi 3. Più di 7 capi
14. Perché acquisti capi di seconda mano?		Prezzi Bassi | Rapporto Qualità Prezzo | Trovare capi unici e cool | Comprare abiti di design e lusso | Sostenibilità Valuta le ragioni proposte su una scala da 1 a 5. **1=Poco Influente, 5=Molto Influente nella mia scelta**
13. In the last three months, how many items of second hand clothes did you buy?		1. Meno di 3 capi 2. Tra i 4 e 6 capi 3. 7 o più di 7 capi

4.3.2 Survey Results

4.3.2.1 Sample Characteristics (n=122)

Table 21: Age Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	16-25 years	55	45.1	45.1	45.1
	26-35 years	37	30.3	30.3	75.4
	36-45 years	11	9.0	9.0	84.4

	46+ years	19	15.6	15.6	100.0
	Total	122	100.0	100.0	

Table 22: Gender Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Female	89	73.0	73.0	73.0
	Male	33	27.0	27.0	100.0
	Total	122	100.0	100.0	

Table 23: Education Level Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than/equal to a High School Diploma	38	31.1	31.1	100.0
	Bachelor Degree	40	32.8	32.8	63.1
	Master Degree	37	30.3	30.3	30.3
	MBA/PhD	7	5.7	5.7	68.9
	Total	122	100.0	100.0	

Table 24: Low Prices

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	10	8.2	8.2	8.2
	2	16	13.1	13.1	21.3
	3	**34**	**27.9**	**27.9**	**49.2**
	4	32	26.2	26.2	75.4
	5	30	24.6	24.6	100.0
	Total	122	100.0	100.0	

Table 25: Price/quality ratio

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1	4	3.3	3.3	3.3

	2	7	5.7	5.7	9.0
	3	27	22.1	22.1	31.1
	4	41	33.6	33.6	64.8
	5	**43**	**35.2**	**35.2**	**100.0**
	Total	122	100.0	100.0	

Table 26: Finding unique items

		Frequency	Percent	Valid Percent	Cumulative Per-cent
Valid	1	6	4.9	4.9	4.9
	2	10	8.2	8.2	13.1
	3	26	21.3	21.3	34.4
	4	34	27.9	27.9	62.3
	5	**46**	**37.7**	**37.7**	**100.0**
	Total	122	100.0	100.0	

Table 27: Buying designer and luxury brands

		Frequency	Percent	Valid Percent	Cumulative Per-cent
Valid	1	16	13.1	13.1	13.1
	2	11	9.0	9.0	22.1
	3	**38**	**31.1**	**31.1**	**53.3**
	4	27	22.1	22.1	75.4
	5	30	24.6	24.6	100.0
	Total	122	100.0	100.0	

Table 28: Sustainability

		Frequency	Percent	Valid Percent	Cumulative Per-cent
Valid	1	13	10.7	10.7	10.7
	2	12	9.8	9.8	20.5
	3	21	17.2	17.2	37.7
	4	25	20.5	20.5	58.2
	5	**51**	**41.8**	**41.8**	**100.0**
	Total	122	100.0	100.0	

Table 29: Income Distribution

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than €800	46	37.7	37.7	37.7
	Between €800 and €1,500	42	34.4	34.4	100.0
	Between €1,500 and €2,000	23	18.9	18.9	59.8
	Between €2,000 and €3,000	7	5.7	5.7	65.6
	More than €3,000	4	3.3	3.3	41.0
	Total	122	100.0	100.0	

Table 30: Frequency of Purchase Distribution (last 3 months)

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Less than 3 items	68	55.7	55.7	80.3
	Between 4 and 6 items	30	24.6	24.6	24.6
	More than 7 items	24	19.7	19.7	100.0
	Total	122	100.0	100.0	

4.3.2.2 Perceptual Map Output

Figure 23: Cumulative Variance Scree Plot

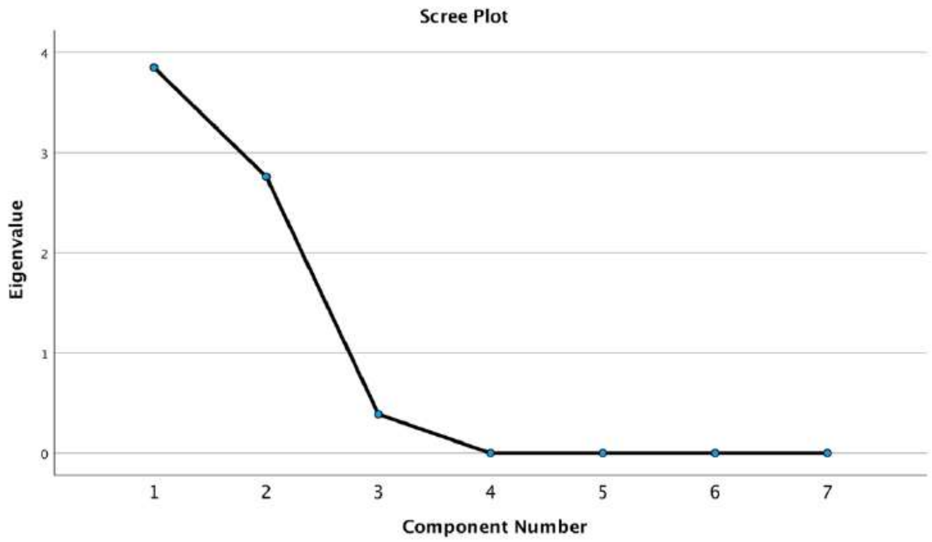


Table 31: Second-Hand Fashion Applications Coordinates

	Component 1	Component 2
Depop	-1.45	-0.36
Vestiaire Collective	0.79	-0.67
Vinted	0.16	1.49
Zalando Second Hand	0.50	-0.46

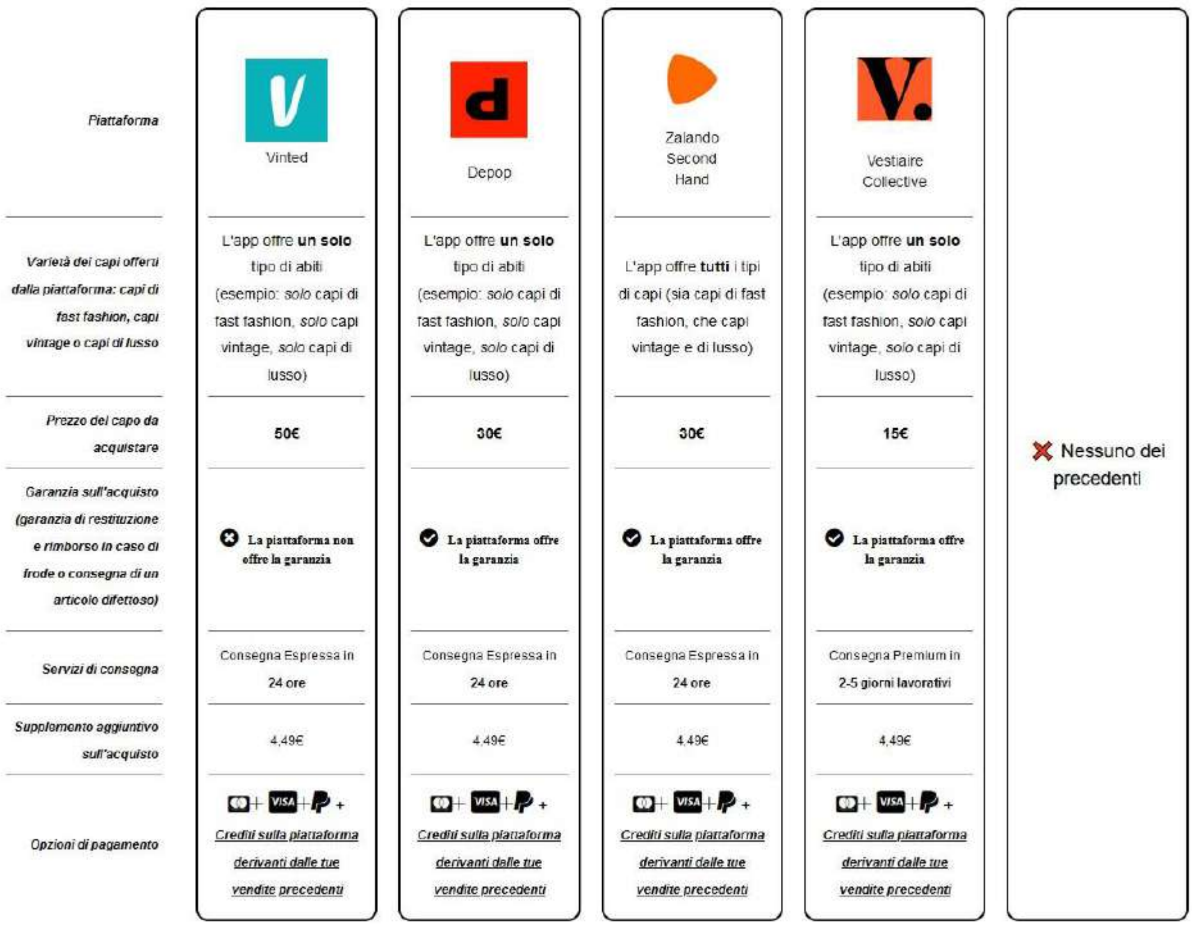
Table 32: Attribute Coordinates

	Component 1	Component 2
Design and Style	0.99	-0.03
Service Quality and Sophistican	0.97	-0.24
Platform Reliability	0.95	-0.18
Items Quality	0.84	-0.29
Sense of Community	0.00	1.00
Price Convenience	0.27	0.95
Fun and Enter-tainement	0.51	0.82

4.4 Conjoint Analysis

4.4.1 Survey Setup

Figure 24: Choice Sets Layout in Conjoint.ly - Italian version



4.4.2 Survey Results

4.4.2.1 Sample Characteristics (n=106)

Figure 25: Respondents Gender Distribution

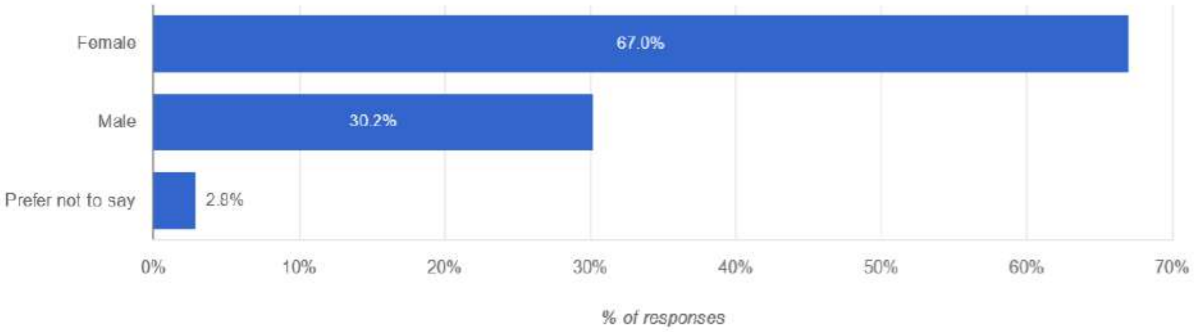


Figure 26: Respondents Age Distribution

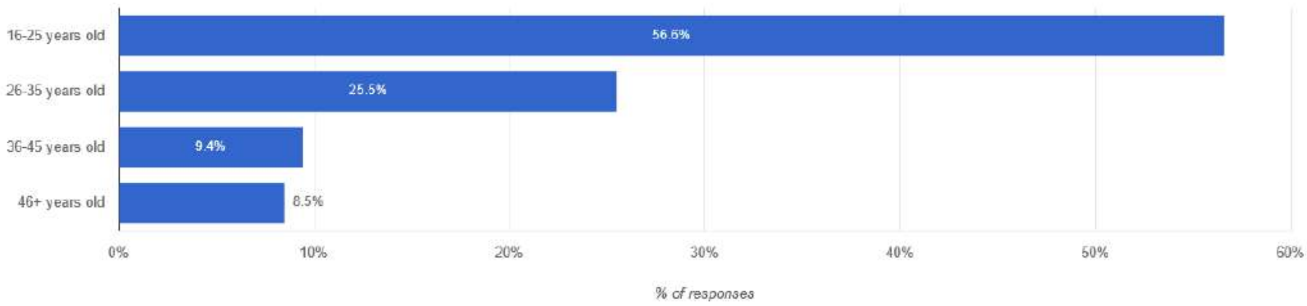


Figure 27: Respondents Education Distribution

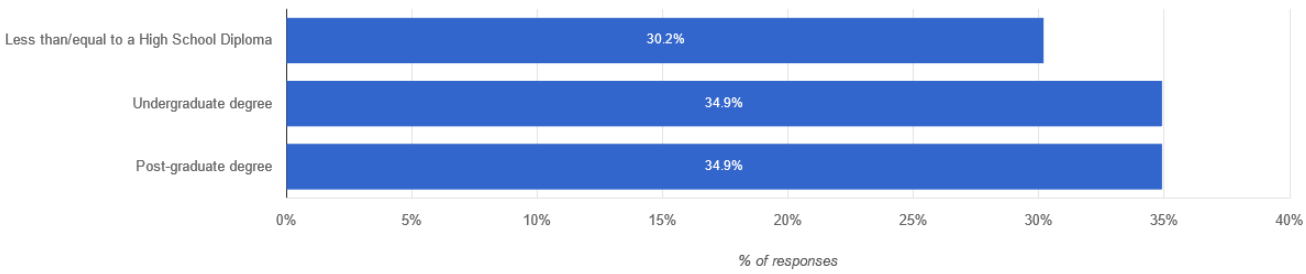


Figure 28: Respondents Income Distribution

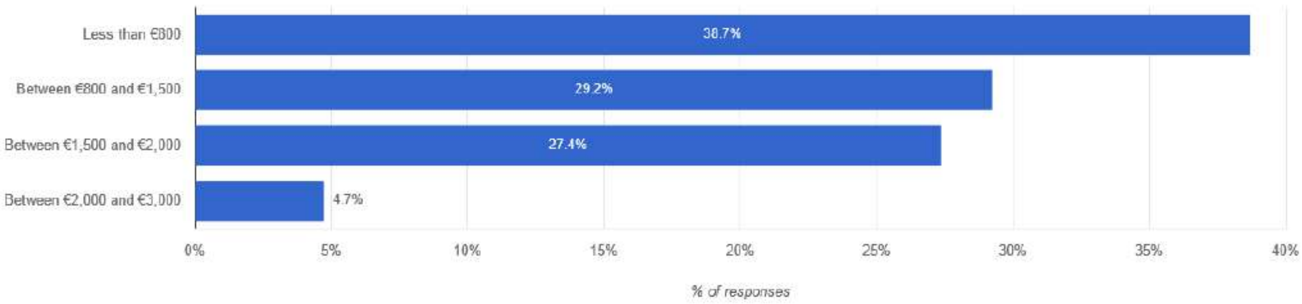


Figure 29: Respondents Frequency of Purchase Distribution

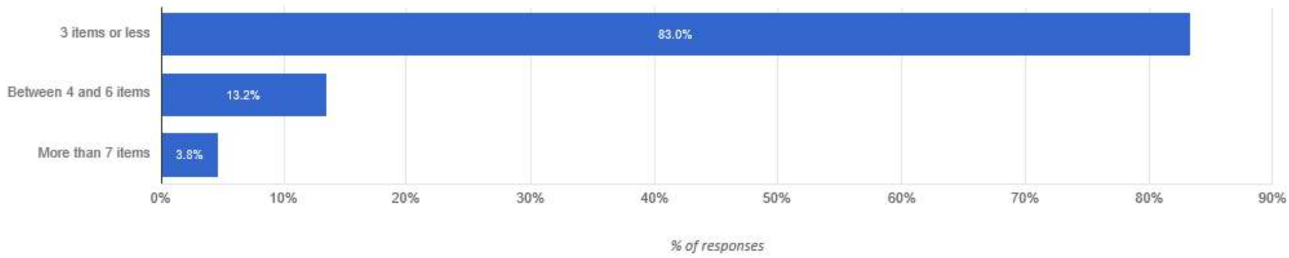


Table 33: Descriptive Statistics - Reasons to Purchase

Option	Minimum	Mean	Median	Mode	Maximum	Standard Deviation
Lower Prices	1	3.7	4	5	5	1.2
Price/Quality Ratio	1	3.6	4	3	5	1.1
Finding Unique Items	1	3.6	4	5	5	1.4
Buying designer and Luxury brands	1	3.1	3	5	5	1.4
Sustainability	1	3.4	3.5	5	5	1.5

4.4.2.2 Conjoint Analysis Output

Table 34: Partworth utilities of all the brands and levels

Attributes	**Levels**	**Vestiaire Collec-tive**	**Zalando**	**Vinted**	**Depop**
1). Variety	Offering only one type of Fashion	(2.8%)	(3.8%)	(4.2%)	(0.6%)
	Offering all types of Fashion	2.8%	3.8%	4.2%	0.6%
2). Product Price	5€	4.1%	3.2%	10.0%	5.7%
	15€	3.1%	11.1%	5.4%	2.7%
	30€	8.0%	(2.1%)	(4.4%)	7.9%

	50€	(15.2%)	(12.2%)	(11.0%)	(16.4%)
3). Buyer Protection	Platform offers the guarantee	17.5%	17.8%	20.6%	18.3%
	Platform does not offer the guarantee	(17.5%)	(17.8%)	(20.6%)	(18.3%)
4). Delivery Services	Express delivery in 24 hours	1.7%	7.2%	4.7%	6.5%
	Premium delivery in 2-5 working days	(1.1%)	(2.2%)	0.2%	(1.8%)
	Basic delivery in 5-10 working days	(0.6%)	(4.9%)	(4.9%)	(4.7%)
5). Additional Fee/Purchase	Free	12.2%	12.7%	9.5%	12.8%
	2,99€	10.6%	(1.0%)	2.8%	2.4%
	4,49€	(3.6%)	(5.4%)	(7.6%)	(7.0%)
	5,99€	(19.1%)	(6.3%)	(4.7%)	(8.1%)
6). Payment Options	Basic: Credit Card + PayPal	(1.0%)	(1.2%)	(1.4%)	(2.9%)
	Advanced: Credit Card + PayPal + Credit on the platform from your previous sales	1.0%	1.2%	1.4%	2.9%

Figure 42: Ranked Concepts List (Conjoint.ly Survey Report)

1	Platform	Variety	Product Pr	Buyer Protection	Delivery Services	Additional fee /purcha	Payment Options	Rank	Value to custom
2	**Zalando Second Hand**	**Offering all types of fashion**	**15€**	**Platform offers the guarantee**	**Express delivery in 24 hours**	**Free**	**Advanced: Credit Card +**	**1**	**82.71362031**
3	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	2	79.33002597
4	**Vinted**	**Offering all types of fashion**	**5€**	**Platform offers the guarantee**	**Express delivery in 24 hours**	**Free**	**Advanced: Credit Card +**	**3**	**74.84717399**
5	Zalando Second Har	Offering only one type of	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	4	71.76778478
6	Zalando Second Har	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	5	71.40241885
7	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	6	70.93831958
8	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	7	69.22256526
9	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	8	68.61585438
10	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	9	68.51296719
11	Zalando Second Har	Offering only one type of	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	10	68.38419045
12	Zalando Second Har	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	11	68.01882452
13	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Basic: Credit Card + Pay	12	65.83897093
14	Vinted	Offering all types of fashi	**5€**	Platform offers the guarantee	Express delivery in 24 hours	**2,99€**	Advanced: Credit Card -	13	65.58389105
15	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Basic delivery in 5-10 working days	Free	Advanced: Credit Card -	14	65.27452496
16	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Basic: Credit Card + Pay	15	64.70699997
17	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	16	64.60411279
18	Zalando Second Har	Offering all types of fashi	**30€**	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	17	63.68200363
19	Vinted	Offering only one type of	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	18	63.2695689
20	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	2,99€	Advanced: Credit Card -	19	62.89823393
21	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	20	62.28164759
22	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Basic delivery in 5-10 working days	Free	Basic: Credit Card + Pay	21	61.89093063
23	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	2,99€	Basic: Credit Card + Pay	22	61.67503664
24	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Basic delivery in 5-10 working days	Free	Advanced: Credit Card -	23	61.49092019
25	Zalando Second Har	Offering only one type of	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	24	60.45658333
26	Zalando Second Har	Offering all types of fashi	30€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	25	60.2984093
27	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	2,99€	Basic: Credit Card + Pay	26	59.5146396
28	Vinted	Offering only one type of	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	27	59.36071449
29	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	2,99€	Advanced: Credit Card -	28	59.35257144
30	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	2,99€	Advanced: Credit Card -	29	59.24968426
31	**Depop**	**Offering all types of fashion**	**30€**	**Platform offers the guarantee**	**Express delivery in 24 hours**	**Free**	**Advanced: Credit Card +**	**30**	**58.37964783**
32	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Basic: Credit Card + Pay	31	58.37279318
33	Zalando Second Har	Offering only one type of	15€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	32	58.27672974
34	Zalando Second Har	Offering all types of fashi	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	33	57.91136381
35	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Basic delivery in 5-10 working days	Free	Basic: Credit Card + Pay	34	57.58206578
36	Zalando Second Har	Offering only one type of	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Basic: Credit Card + Pay	35	57.072989
37	Vinted	Offering only one type of	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	Free	Advanced: Credit Card -	36	57.03824929
38	Vinted	Offering only one type of	15€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	37	56.93536211
39	Depop	Offering only one type of	30€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	38	56.71572635
40	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	4,49€	Advanced: Credit Card -	39	56.62296417
41	Depop	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	Free	Advanced: Credit Card -	40	55.54320596
42	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Premium delivery in 2-5 working da	2,99€	Basic: Credit Card + Pay	41	55.44371703
43	Zalando Second Har	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	5,99€	Advanced: Credit Card -	42	55.35046894
44	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Express delivery in 24 hours	2,99€	Basic: Credit Card + Pay	43	55.34082985
45	Vinted	Offering all types of fashi	5€	Platform offers the guarantee	Express delivery in 24 hours	5,99€	Advanced: Credit Card -	44	55.23346377
46	**Vestiaire Collective**	**Offering all types of fashion**	**30€**	**Platform offers the guarantee**	**Express delivery in 24 hours**	**Free**	**Advanced: Credit Card +**	**45**	**55.22039262**
47	Vinted	Offering all types of fashi	15€	Platform offers the guarantee	Basic delivery in 5-10 working days	Free	Advanced: Credit Card -	46	55.15671339

4.4.2.3 Conjoint Analysis Simulations Output

Figure 30: Sensitivity to Product Price - Zalando Second Hand

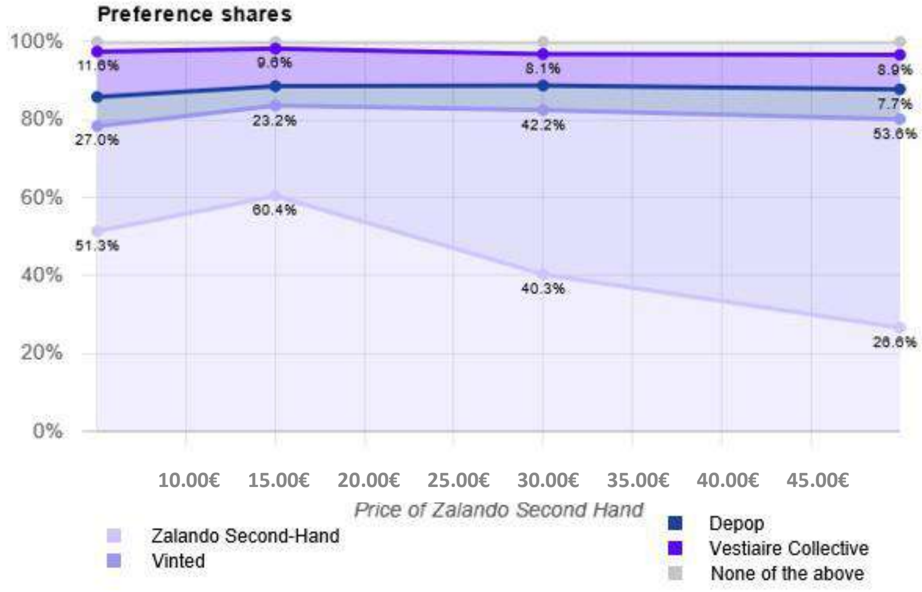


Figure 31: Sensitivity to Product Price – Vinted

Figure 32: Sensitivity to Product Price - Depop

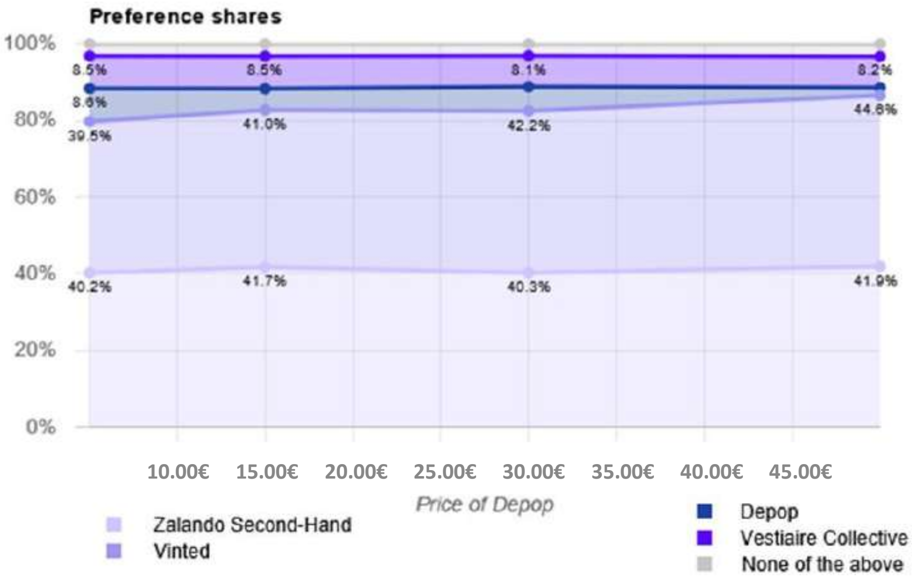


Figure 33: Sensitivity to Product Price - Vestiaire Collective

Figure 34: Sensitivity to Additional Fees - Zalando Second-Hand

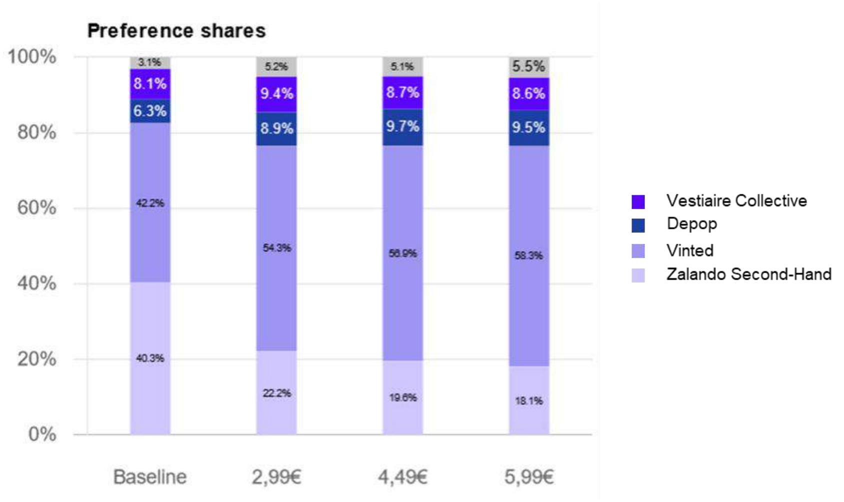


Figure 35: Sensitivity to Additional Fees - Vinted

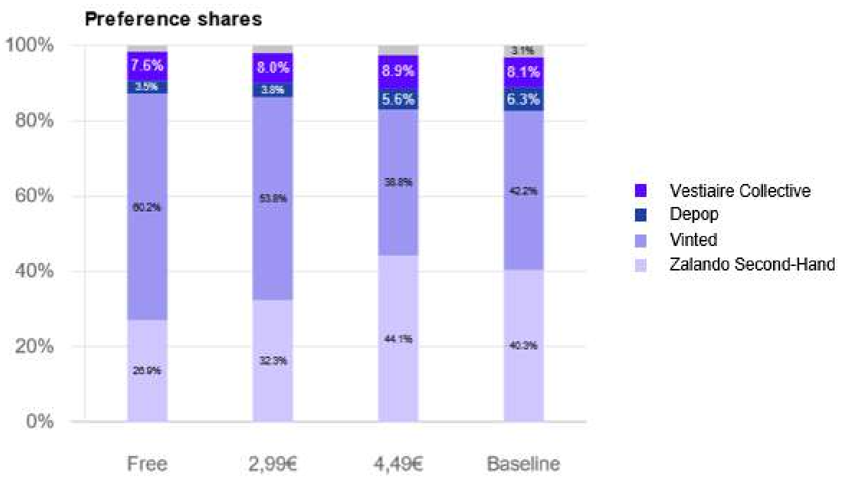


Figure 36: Sensitivity to Additional Fees - Depop

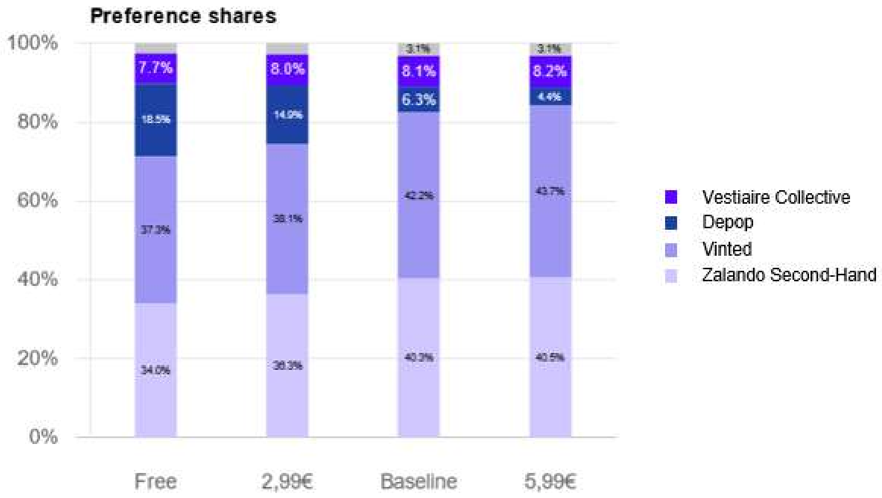


Figure 37: Sensitivity to Additional Fees - Vestiaire Collective

Figure 38: Sensitivity to Buyer Protection - Zalando Second-Hand

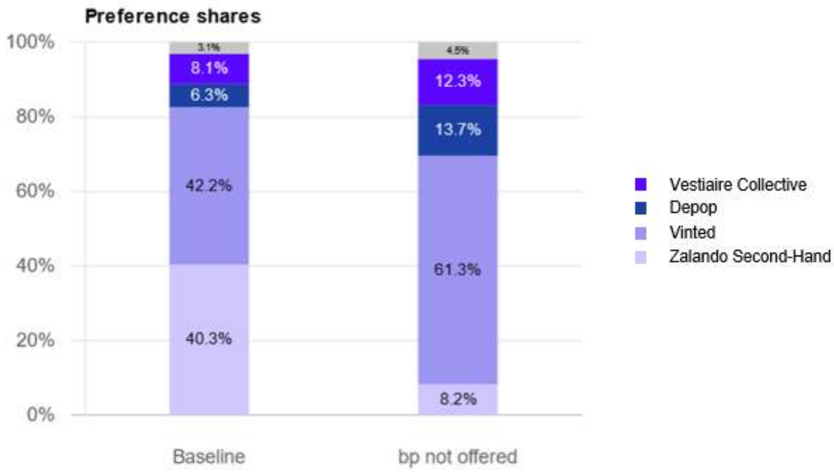


Figure 39: Sensitivity to Buyer Protection - Vinted

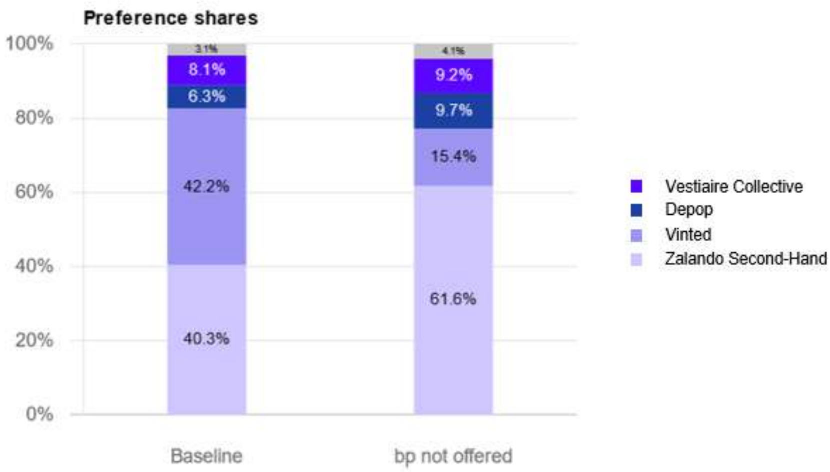


Figure 40: Buyer Protection Sensitivity - Depop

Figure 41: Buyer Protection Sensitivity - Vestiaire Collective

4.5 Consumer Segments: Clustering

Table 35: K-Means Clustering - Number of clusters

Number of Cases in each Cluster

Cluster	1	60.000
	2	25.000
	3	72.000
	4	71.000
Valid		228.000
Missing		.000

Table 36: K- Means Clustering – Final clusters center

Final Cluster Centers

	Cluster			
	1	2	3	4
Gender	.22	.48	.20	.35
Age	1.58	1.80	2.56	1.32
Education	2.10	1.3	2.10	2.01
Income	2.10	2.00	2.40	1.52
Frequency	1.2	1.16	1.68	1.35
Lower Prices	2.93	3.52	3.19	4.00
Price Quality Ratio	3.48	2.76	4.06	4.06
Finding Unique Cool Items	4.30	1.60	4.29	3.1
Buying Designer/Luxury	3.92	1.72	4.21	2.25
Sustainability	2.05	2.00	4.49	4.46

Table 37: ANOVA

ANOVA

	Cluster		Error			
	Mean Square	df	Mean Square	df	F	Sig.
Gender	.658	3	.199	224	3.312	.021
Age	19.919	3	.812	224	24.527	<.001
Education	.375	3	.667	224	.562	**.641**
Income	9.519	3	.868	224	10.967	<.001
Frequency	2.332	3	.469	224	4.969	.002
Lower Prices	12.875	3	1.327	224	9.703	<.001
Price Quality Ratio	14.038	3	.978	224	14.352	<.001
Finding Unique Cool Items	53.532	3	.969	224	55.224	<.001
Buying Designer/Luxury	73.938	3	.870	224	84.963	<.001
Sustainability	105.838	3	.645	224	164.070	<.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.

Table 38: Cluster 1 - Descriptive Statistics

Statistic	Gender (Male=1)	Age (1-4)	Education (1-3)	Income (1-4)	Frequency (1-3)	Lower Prices	Price/Quality Ratio	Finding Unique and Cool Items	Buying designer and Luxury brands	Sustainability
Nbr. of observations	60	60	60	60	60	60	60	60	60	60
Minimum	0,000	1,000	1,000	1,000	1,000	1,000	1,000	2,000	1,000	1,000
Maximum	1,000	4,000	3,000	4,000	3,000	5,000	5,000	5,000	5,000	4,000
1st Quartile	0,000	1,000	2,000	1,000	1,000	2,000	3,000	4,000	3,000	1,000
Mean	0,217	1,583	2,100	2,100	1,367	2,933	3,483	4,300	3,917	2,050
Standard deviation (n-1)	0,415	0,869	0,730	0,877	0,637	1,071	1,000	0,908	1,013	0,832

Table 39: Cluster 2 - Descriptive Statistics

Statistic	Gender (Male=1)	Age (1-4)	Education (1-3)	Income (1-4)	Frequency (1-3)	Lower Prices	Price/Quality Ratio	Finding Unique and Cool Items	Buying designer and Luxury brands	Sustainability
Nbr. of observations	25	25	25	25	25	25	25	25	25	25
Minimum	0,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Maximum	1,000	4,000	3,000	4,000	2,000	5,000	5,000	4,000	3,000	4,000
1st Quartile	0,000	1,000	1,000	1,000	1,000	3,000	2,000	1,000	1,000	1,000
Median	0,000	2,000	2,000	2,000	1,000	4,000	3,000	1,000	2,000	2,000
3rd Quartile	1,000	2,000	3,000	3,000	1,000	5,000	4,000	2,000	2,000	3,000
Mean	0,480	1,800	1,880	2,000	1,160	3,520	2,760	1,600	1,720	2,000
Variance (n-1)	0,260	0,917	0,777	0,917	0,140	2,010	1,357	0,833	0,627	1,000
Standard deviation (n-1)	0,510	0,957	0,881	0,957	0,374	1,418	1,165	0,913	0,792	1,000

Table 40: Cluster 3 - Descriptive Statistics

Statistic	Gender (Male=1)	Age (1-4)	Education (1-3)	Income (1-4)	Frequency (1-3)	Lower Prices	Price/Quality Ratio	Finding Unique and Cool Items	Buying designer and Luxury brands	Sustainability
Nbr. of observations	72	72	72	72	72	72	72	72	72	72
Minimum	0,000	1,000	1,000	1,000	1,000	1,000	1,000	2,000	2,000	2,000
Maximum	1,000	4,000	3,000	5,000	3,000	5,000	5,000	5,000	5,000	5,000
1st Quartile	0,000	2,000	1,000	2,000	1,000	3,000	3,000	4,000	4,000	4,000
Median	0,000	2,000	2,000	2,000	1,000	4,000	4,000	4,000	4,000	5,000
3rd Quartile	0,000	4,000	3,000	3,000	2,250	5,000	5,000	5,000	5,000	5,000
Mean	0,208	2,556	2,097	2,403	1,681	3,694	4,056	4,292	4,208	4,486
Variance (n-1)	0,167	1,264	0,793	1,230	0,728	1,567	1,011	0,660	0,646	0,535
Standard deviation (n-1)	0,409	1,124	0,891	1,109	0,853	1,252	1,005	0,813	0,804	0,731

Table 41: Cluster 4 - Descriptive Statistics

Statistic	Gender (Male=1)	Age (1-4)	Education (1-3)	Income (1-4)	Frequency (1-3)	Lower Prices	Price/Quality Ratio	Finding Unique and Cool Items	Buying designer and Luxury brands	Sustainability
Nbr. of observations	71	71	71	71	71	71	71	71	71	71
Minimum	0,000	1,000	1,000	1,000	1,000	1,000	2,000	1,000	1,000	2,000
Maximum	1,000	4,000	3,000	4,000	3,000	5,000	5,000	5,000	4,000	5,000
1st Quartile	0,000	1,000	1,000	1,000	1,000	3,000	3,000	3,000	1,000	4,000
Median	0,000	1,000	2,000	1,000	1,000	4,000	4,000	3,000	2,000	5,000
3rd Quartile	1,000	2,000	3,000	2,000	2,000	5,000	5,000	5,000	3,000	5,000
Mean	0,352	1,324	2,014	1,521	1,352	4,000	4,056	3,465	2,254	4,465
Variance (n-1)	0,231	0,365	0,614	0,567	0,374	1,000	0,797	1,452	1,049	0,595
Standard deviation (n-1)	0,481	0,604	0,784	0,753	0,612	1,000	0,893	1,205	1,024	0,771

4.6 Cluster-Specific Conjoint Analysis

Table 42: Cluster Specific Partworth Utilities

	Variety		Product Price				Buyer Protection		Delivery			Additional Fee				Payment Options	
	NotAllTypes	AllTypes	5 €	15 €	30 €	50 €	yes	no	24h	2-5 working days	5-10 working days	free	2,99€	4,49€	5,99€	CreditCard + PayPal	Credit Card + PayPal + Credit on the platform from previous sales
Cluster 1																	
Vestiaire	-0.2%	0.2%	-5.7%	-4.3%	13.6%	-3.5%	21.8%	-21.8%	0.2%	-1.3%	1.1%	8.6%	12.8%	-2.5%	-18.8%	-1.3%	1.3%
Zalando	-2.6%	2.6%	-4.8%	8.0%	2.5%	-5.6%	23.8%	-23.8%	9.5%	-3.7%	-5.9%	11.0%	-2.9%	-5.6%	-2.4%	-0.8%	0.8%
Vinted	-5.4%	5.4%	4.7%	3.2%	-1.1%	-6.8%	23.3%	-23.3%	7.3%	-2.7%	-4.6%	9.3%	2.8%	-7.6%	-4.5%	-1.1%	1.1%
Depop	-0.8%	0.8%	-1.1%	-3.5%	11.5%	-6.9%	20.4%	-20.4%	9.5%	-2.2%	-7.2%	10.0%	-0.6%	-3.9%	-5.6%	-3.4%	3.4%
Average	-2.3%	2.3%	-1.7%	0.8%	6.6%	-5.7%	22.3%	-22.3%	6.6%	-2.5%	-4.1%	9.7%	3.0%	-4.9%	-7.8%	-1.7%	1.7%
Cluster 2																	
Vestiaire	-1.0%	1.0%	6.8%	3.1%	9.7%	-19.6%	13.4%	-13.4%	2.3%	-0.8%	-1.5%	14.2%	11.7%	-4.7%	-21.2%	1.4%	-1.4%
Zalando	-3.2%	3.2%	4.6%	13.9%	-2.7%	-15.7%	11.6%	-11.6%	8.8%	-2.3%	-6.5%	13.1%	-0.3%	-3.4%	-9.4%	-1.4%	1.4%
Vinted	-3.8%	3.8%	11.3%	8.4%	-4.0%	-15.7%	17.6%	-17.6%	4.4%	1.5%	-5.9%	9.1%	1.2%	-7.8%	-2.4%	-1.5%	1.5%
Depop	0.8%	-0.8%	7.0%	7.3%	9.2%	-23.6%	13.8%	-13.8%	6.0%	-4.1%	-1.8%	13.9%	5.4%	-6.5%	-12.8%	-0.6%	0.6%
Average	-1.8%	1.8%	7.4%	8.2%	3.0%	-18.7%	14.1%	-14.1%	5.4%	-1.4%	-3.9%	12.6%	4.5%	-5.6%	-11.5%	-0.5%	0.5%
Cluster 3																	
Vestiaire	-3.1%	3.1%	1.5%	4.0%	7.0%	-12.4%	19.0%	-19.0%	1.8%	0.0%	-1.9%	10.1%	10.4%	-2.2%	-18.3%	-2.0%	2.0%
Zalando	-5.9%	5.9%	1.6%	10.2%	-2.3%	-9.5%	19.9%	-19.9%	6.0%	-3.3%	-2.6%	11.8%	-1.6%	-4.8%	-5.4%	-1.1%	1.1%
Vinted	-4.9%	4.9%	8.4%	3.5%	-4.0%	-7.9%	22.5%	-22.5%	4.3%	0.3%	-4.6%	9.9%	0.8%	-7.0%	-3.6%	-1.6%	1.6%
Depop	-1.3%	1.3%	5.0%	1.6%	6.7%	-13.3%	20.6%	-20.6%	6.7%	-1.3%	-5.5%	12.4%	-0.8%	-5.5%	-6.1%	-2.8%	2.8%
Average	-3.8%	3.8%	4.1%	4.8%	1.8%	-10.8%	20.5%	-20.5%	4.7%	-1.1%	-3.7%	11.0%	2.2%	-4.9%	-8.4%	-1.9%	1.9%
Cluster 4																	
Vestiaire	-4.55%	4.55%	10.29%	7.51%	2.94%	-20.75%	12.55%	-12.55%	1.97%	-1.21%	-0.76%	13.50%	6.55%	-4.41%	-15.63%	-1.23%	1.23%
Zalando	-3.51%	3.51%	8.91%	12.43%	-4.76%	-16.58%	14.30%	-14.30%	5.31%	-0.19%	-5.12%	14.18%	0.13%	-6.14%	-8.17%	-1.30%	1.30%
Vinted	-4.12%	4.12%	10.01%	5.19%	-4.40%	-10.80%	20.65%	-20.65%	4.68%	0.30%	-4.98%	9.53%	3.01%	-7.69%	-4.85%	-1.39%	1.39%
Depop	-0.49%	0.49%	11.00%	6.61%	4.13%	-21.75%	15.11%	-15.11%	3.12%	-0.29%	-2.83%	13.59%	5.32%	-10.40%	-8.51%	-3.05%	3.05%
Average	-3.17%	3.17%	10.05%	7.94%	-0.52%	-17.47%	15.65%	-15.65%	3.77%	-0.35%	-3.42%	12.70%	3.75%	-7.16%	-9.29%	-1.74%	1.74%

Table 43: Attribute Importance per Cluster

	Variety	Price	Buyer Pro-tection	Fee	Delivery	Payment
Cluster 1						
Vestiaire	8.65%	26.69%	26.41%	23.32%	8.80%	6.13%
Zalando	5.26%	20.50%	31.63%	19.01%	16.28%	7.32%
Vinted	8.68%	23.52%	31.22%	17.00%	14.85%	4.72%
Depop	3.92%	28.28%	24.66%	21.27%	15.57%	6.30%
Average	6.63%	24.75%	28.48%	20.15%	13.88%	6.12%
Cluster 2						
Vestiaire	8.84%	24.33%	20.78%	31.92%	8.50%	5.62%
Zalando	5.97%	25.79%	22.09%	22.40%	17.74%	6.01%
Vinted	6.49%	28.97%	25.50%	17.78%	15.40%	5.86%
Depop	5.02%	28.37%	20.00%	26.09%	13.77%	6.75%
Average	6.58%	26.87%	22.09%	24.55%	13.85%	6.06%
Cluster 3						
Vestiaire	8.84%	21.35%	27.72%	26.19%	9.10%	6.79%
Zalando	9.05%	19.12%	32.15%	19.35%	12.64%	7.69%
Vinted	8.28%	22.68%	33.11%	17.61%	14.70%	3.63%
Depop	5.50%	23.93%	27.05%	22.30%	13.55%	7.67%
Average	7.92%	21.77%	30.01%	21.36%	12.50%	6.44%
Cluster 4						
Vestiaire	8.75%	27.63%	22.83%	28.19%	7.91%	4.69%
Zalando	7.38%	24.94%	26.32%	22.30%	12.76%	6.29%
Vinted	7.38%	26.51%	29.97%	17.91%	13.70%	4.53%
Depop	3.93%	31.30%	22.53%	25.39%	10.72%	6.14%
Average	6.86%	27.59%	25.41%	23.45%	11.27%	5.41%