Online boutique stores: what factors drive product recommendations in limited-edition resale markets?

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Management Summary

This study examines product recommendations (e.g.: ”items you may like”) in the limited-edition fashion resale industry. With a staggering growth of consumers seeking to acquire luxurious secondhand fashion products, this industry has seen an uprise in platforms that meet this demand. While previous research has explored the impact of product recommendations on platforms such as Amazon, this study aims to extend this line of inquiry to this new industry where exclusivity and scarcity of items are admired. These aspects present a challenge for online retailers in balancing high-revenue generating products with unique offerings in their product recommendations. Therefore, the knowledge on product recommendations is expanded in two ways by this research: (1) Finding how product revenue and the recommendation count a product attains are related, and how these differ across types of product recommendation lists. (2) Delving into brand characteristics (assortment size and luxury aspect) of each brand offered, and analyzing whether these features are related to increased recommendation count of an item.

To investigate these relationships, product recommendations and historical purchase data were collected from GOAT, one of the industry leaders. The data was then transformed into a final dataset consisting of 5,657 uniquely recommended products across 96 fashion brands. The analysis was conducted by performing two stages of regression on the final data set.

The results of the study indicate that the recommendation count of an item in product recommendations is related to the amount of revenue it generates for the platform. However, the type of recommendation list plays a significant role in this relationship. Bestseller recommendation lists have more items with a high count of recommendations and high revenue. In contrast, algorithmic recommendation lists have a wider distribution of uniquely offered items with lower revenue-generating products. Additionally, the study found that brands with a larger assortment size attain a higher amount of product recommendations. Niche luxury brands are not confirmed to be less represented in the platform’s recommendations compared to more mainstream brands.

Contents

1 Introduction

When you observe the inside of a fashion boutique store, you may see everything is carefully crafted to attract and engage customers with exclusive products. Items are often displayed in an aesthetically pleasing way, and each item has its own space to shine. Not to forget shopping assistants provide exceptional consultation about costly products to customers. Recently, the online equivalent of the boutique store has been gaining significant traction, with an estimated value of 40 billion dollars for the total market of limited-edition fashion resale (Statista, 2022). Innovative resale platforms such as ”Vestiaire Collective”, ”The RealReal” and ”GOAT” make it easy to buy exclusive fashion items instantly. A crucial aspect is that these platforms are peer-to-peer, and therefore enable customers worldwide to sell items. This makes the range of products far beyond what a physical store can offer. Like physical stores, ”Online boutique stores” have their way to engage their audience, with most platforms having algorithmic product recommendations (e.g.: ”items you may like”). Yet, these recommendation algorithms typically overrepresent the same popular items in their assortment (Oestreicher-Singer et al., 2013). The failure to represent the unique offerings represents a significant missed opportunity in organizing the digital store environment within this industry.

Offering a wide range of products is essential for online stores in general, as it not only plays a crucial role in strategic positioning among competitors but also has the potential to increase consumer welfare. This is supported by research from ElMaraghy et al. (2013) and Brynjolfsson et al. (2003), who highlight the benefits of providing a large variety of items to customers. According to an industry report by McKinsey, finding rare and iconic items is even more important than all other aspects of the fashion resale market (Berg et al., 2021). The purchase process of hedonic products such as luxury items in general involves experiencing products through discovery and browsing many pages (Li et al., 2020). The typical recommendation set of popular items, therefore, does not align with the uniqueness that consumers seek in products. Meanwhile, product recommendations are a great tool to help customers by reducing search costs in acquiring items (Chris, 2006). Recent evidence also shows that users purchase products through product recommendations because it expands the breadth of consideration sets for customers (Li et al., 2021). This suggests that consumers and companies both benefit from offering variety through product recommendations. Another crucial aspect of offering variety for this particular market is because of the scarcity of items offered. For any type of product, demand increases when being recommended on another product's page (Lin et al., 2017). In the case of online fashion resale, prices highly fluctuate based on scarcity (Park et al., 2022). Potentially, the increase in demand from product recommendations increases the purchase price of the product. This arguably is a negative event, as consumers typically want to purchase products for cheap prices. As final evidence for the importance of this study, offering a more diverse set of items through recommendations has already been a notified objective for some fashion resale platforms themselves (Sá et al., 2022). Knowing what specific factors drive the number of recommendations for a product, and thereby affect the diversity of products offered could guide strategies concerning the presentation of online stores for this specific industry.

This study is connected to the existing literature about the drivers of product recommendations, where an important aspect is found to be the relevancy of products, closely tied to the popularity and revenue a product generates (Oestreicher-Singer and Sundararajan, 2012; Oestreicher-Singer et al., 2013). Furthermore, the algorithms that are constructed with different personalization, impact product recommendations per user (Su and Khoshgoftaar, 2009; Leskovec et al., 2014). Popularity in product recommendations also shows to be related to a less diverse of items represented (Zhu et al., 2022). Product recommendations furthermore have ”cross-pollination” between genres on product pages, which results in one mainstream genre affecting the consumption of another niche genre, by mediating more purchases because of their favor over another genre (Lee and Hosanagar, 2019, 2014). Studies have been carried out mainly on recommendation lists using collaborative filtering (CF) algorithms, with no significant findings yet on purchase behavior for other types such as ”bestseller lists” that present a curated list of items based on how trending they are (Li et al., 2021).

Despite this extensive research on product recommendations, this study focuses on offering more consistency in the relationship between product revenue as a driver for product recommendations, and examining what other factors make a product attain product recommendations. Due to the context of the fashion resale industry, a heavy emphasis on brands is also expected in driving product recommendations.

The current knowledge of the effects of recommendation systems on consumption is expanded in two ways by this research: (1) Finding how product revenue and the recommendation count[1] a product attains are related, and how these differ across types of product recommendation lists. (2) Delving into brand characteristics (assortment size and luxury aspect) of each brand offered, and analyzing whether these features are related to increased recommendation count of an item.

The data used is a recently collected dataset from a leading limited-edition apparel & sneaker platform: *GOAT.com*. More specifically, a sample across product pages was drawn to collect product recommendations across CF and bestseller recommendation lists. After processing the data, a dataset of 5,657 uniquely recommended products across 96 different fashion brands was formed. From this dataset, a model-free analysis is performed in this study to examine the relationship between the main constructs. Next, a two-stage regression analysis follows between product revenue on recommendation count, brands, and interactions with the different list types that appear on *GOAT*. This shows different effects between the list types and brands included in the model. Secondly, the brand intercepts found in this model are regressed on specific brand characteristics, which shows that assortment size is positively related, and luxury aspect is negatively related to the count of recommendations.

In the next chapters, an overview of related literature is given, followed by the expectations of this research and a more comprehensive description of the data and models used. Finally, outcomes are given regarding this study, with a discussion about limitations and managerial implications.

[1]Number of times a product appears as a recommendation across product pages of a website.

2 Literature review

This chapter aims to provide a comprehensive understanding of product recommendations by reviewing relevant literature. Multiple factors play a role in determining which product recommendations are displayed and how frequently they appear. Therefore, this chapter explores the various factors that drive product recommendations, all of which aligns with the research question at hand.

2.1 Main drivers of product recommendations

Relevancy

One stream of literature on product recommendations is concerned with the design of algorithms that show the most relevant products in online stores (He and Chu, 2010; Sá et al., 2022). Although recommendations are constructed by an online retailer and depend on the design choices of the online store owner, there is overlap in what factors influence how often a product is shown. Retailers such as Amazon provide relevant product recommendations with the main objective of offering a fitting product for the user (Linden et al., 2003). A big determinant of relevance is the previous engagement of other users, which can be due to behavior such as previous clicks, as well as previous purchases and ratings (Lee and Hosanagar, 2019). The previous engagement suggests that popular products with more sales are more relevant, and therefore featured more often as a recommendation. This can be confirmed by previous research, as Oestreicher-Singer et al. (2013) found that bestseller products (those with high revenues) obtain revenues from direct purchases from users, but also for a substantial part by being featured as a recommendation on other pages. This increase in product revenue reinforces even more recommendations since they are picked up to become more relevant, referred to as the ”rich-get-richer effect” (Fleder and Hosanagar, 2009).

Personalization

A second dimension that drives product recommendations is how online retailers add personalization elements to increase relevance to users. The degree of personalization per user can play a role in what is featured in the ”recommended” section. Online retailers often take into account the individual user profile and previous purchases of a user with a higher chance of a purchase (Su and Khoshgoftaar, 2009). The recommendations can be formed based on users with similar profiles instead of basing this on the collective engagement of the website, which is done in a mechanism called collaborative filtering (CF). The profile of a user is often determined by analyzing user behavior such as clicks or purchases, and interaction with specific brands or categories of items. The counterpart of CF is content-based filtering, which relies on item features such as color, or ratings to recommend similar products (Leskovec et al., 2014). This mechanism can solely be based on the similarity of products. The emphasis of this method however is on the item features, rather than on feedback from other users. Lastly, there are systems where both item features and CF is used, with Amazon implementing this system as their main way of optimizing product recommendations (Linden et al., 2003). Personalization is thus a way to increase relevancy for a specific user, and to account for a heterogeneous customer base.

Popularity

Recent research has highlighted the significance of incorporating both popular and unpopular products as a third dimension in developing recommendation algorithms. This is due to a common bias that arises in personalized and non-personalized systems, where the most popular items are recommended more frequently than other products (Leskovec et al., 2014; Sá et al., 2022; Chen et al., 2023). Collaborative filtering recommendation systems are particularly prone to this bias since previous clicks and purchases guide recommendations, unlike content-based systems that prioritize content over sales. Consequently, even with personalization, the algorithm tends to overrepresent popular items (Abdollahpouri et al., 2021). A small stream of literature so far has focused on measuring the popularity of product recommendations, specifically on content-based recommendations for vacation destinations (Zhu et al., 2022). This is done through the metric of "market competition". Market competition in this context means to what extent sellers of products "compete" to be shown in a recommendation list. As there are typically only a handful of recommendations that consumers can pay attention to on a page, this can be expressed as competition among products. In the scenario that every product on the platform of a certain category makes equal sales, the competition is expected to be high. The opposite of low competition holds when a few products attain most of the sales. The study outcomes suggest that when the demand for products increases, the competition is lower. This is similar to what Oestreicher-Singer et al. (2013) found in the case of bestseller books on Amazon, which are represented to a great extent in the number of recommendations, because of their high relevance to the user. A key difference between the studies is that the latter had co-purchases, meaning that both the focal item and the recommended item are purchased. In the case of substitute products (replacements of each other), such as vacations, consumers switch to the recommended product, which has varying effects on the demand for products (Zhu et al., 2022; Kumar and Hosanagar, 2019). In the study from Oestreicher-Singer et al. (2013) there are also reviews present next to the recommended products, which are endogenous to the popularity (Lee and Hosanagar, 2021a). Another difference in the studies is that in the study of Zhu et al. (2022) content-based filtering is used, and just the degree of competition is reported. This doesn't have the same implications as whether the popularity of a product is related to being recommended more often. The gap in this research is thus finding more consistency in popularity and product revenue as a driver for product recommendations.

2.2 Related factors of product recommendations

Different mediation effects

It is also worth considering the stream of literature about what makes a recommendation be bought by consumers, which is done primarily by experimental studies on product recommendation systems. Recommendations mediate transactions by bringing awareness of a product, and salience, which is about the incentive for the user to purchase (Lee and Hosanagar, 2021a). However, there is also evidence that new items that users discover are the reason for purchase, rather than mere exposure to an item (Li et al., 2021). Consumers from that perspective buy because the recommended options are a better choice. For products hedonic of nature and focused on experience (e.g.: jewelry) the conversion rate is higher than for products that are utilitarian and focused on search (e.g.: toilet paper) (Lee and Hosanagar, 2021b). The hedonic/utilitarian dimension indicates the end goal of the product; whether for enjoyment or practical usage. The search/experience dimension indicates to what extent the quality of the product can be judged before making a purchase, which is high for search products and low for experience products. As mentioned in the previous subchapter, product competition can be influenced by factors such as popularity and reviews (Oestreicher-Singer et al., 2013). There is also evidence that consumption diversity, which can be considered the opposite of competition in the context of product variety, is affected by other products (Lee and Hosanagar, 2014). Specifically, the diversity of items consumed declines as a consequence of certain genres being favored (cross-pollination). This means that when the genre ”comedy” is shown as a recommendation, consumers switch to purchasing this comedy movie, which results in less diversity of products overall. The findings in these experimental studies highlight a critical point that both sales and diversity are affected as a consequence of product recommendations.

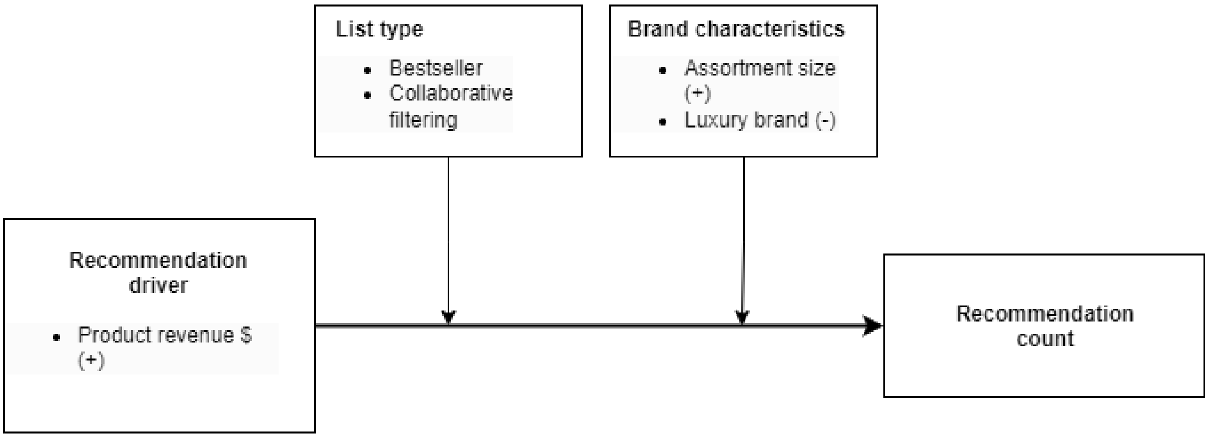
Recommendation list types

Besides the algorithm a retailer deploys there is another way in which a shop can influence product recommendations, which is through the type of list they are presented in, e.g.: ”People who bought this item”, or ”trending items in this category” (Su and Khoshgoftaar, 2009). The critical difference between these lists depends on the context in which they are presented. Therefore, they can be considered as another way to curate products. Varying effects between these lists and consumption also exist. For example, Lee and Hosanagar (2019) found that for collaborative filtering lists that were based on purchases, compared to views of users, the effect on consumption of recommendations is greater. Most of the earlier-mentioned studies focus on different collaborative filtering implementations, such as co-purchase items (Oestreicher-Singer et al., 2013). The exception is Zhu et al. (2022), which studied factors that influence competition for content-based recommendation lists. The studies presented so far have all focused on a single list, but have not considered multiple lists occurring on the same page. Likewise, the experimental studies on product recommendations, all used a single type of recommendation list as a treatment, with no list present as a control group. In the study of Li et al. (2021), no conclusion could be drawn about the different effects between best-selling lists of product recommendations compared to lists based on CF. This leaves a gap in the literature to explore differences between different list types used in product recommendations.

3 Conceptual framework

In this section, the framework to measure what factors influence product recommendations is discussed. The figure presented below illustrates the anticipated connections among the variables examined in this research, and each relationship is described in greater detail in this chapter.

Figure 1: Conceptual model



3.1 Expectations

3.1.1 Main driver of recommendation count

The construction of the product recommendation algorithm hugely affects how often a product is recommended, with the main mechanisms based on past user feedback such as previous purchases (Su and Khoshgoftaar, 2009; Linden et al., 2003). A common effect of these systems is that products that are sold frequently are most often present in recommendations, compared to less popular items. This is because these recommendations thrive on past user feedback and demand significantly increases for a product when it is featured as a recommendation on another product page (Oestreicher-Singer and Sundararajan, 2012). A "rich-get-richer effect" therefore tends to occur for products that are among the most popular ones (Fleder and Hosanagar, 2009; Taeuscher, 2019). This means that products that are sold often and that are well-reputed, accumulate even more sales over time. This effect has shown the potential to shift the number of recommendations to the top revenue-generating product in product recommendation lists (Oestreicher-Singer et al., 2013). Another reason why the revenue an item generates could contribute to the times it is present in a recommendation list is that it could benefit the online retailer from a profit perspective. Typically, online marketplaces work on commission-based sales, meaning that a percentage of an item's sale is taken as a fee for the seller (Choi and Mela, 2019). The placement of items in recommendation lists is therefore important to consider as an online retailer and can influence aggregate revenues. This might incentivize online retailers to favor items that are generating high revenues, as they expect an even higher demand through product recommendations. The expectation is that based on the favoritism for often sold items, the recommendation count a specific item attains is positively related to that of the average revenue it generates.

3.1.2 Difference between product recommendation list types

Since lists take on several forms such as "items you may like" or "People who bought this item", the implications for the previous expectation could very well depend on the type of list present. Since one of the considerations in collaborative filtering is to account for less popular products, the distribution of items might be spread out more evenly (Linden et al., 2003). Moreover, bestseller lists represent the same list of items on multiple product pages, related to a brand or category of that product. This means that overall the product recommendations are more of the same type of products. Lists based on collaborative filtering seem to be somewhat biased in suggesting items due to popularity entering the algorithm (Abdollahpouri et al., 2021). However, generally provide suggestions based on specific features of a product, which should provide a wider variety of items. There is evidence of differences between types of collaborative filtering lists in e-commerce settings on product sales and diversity (i.e.: "Customers who bought this item also bought" or Customers who viewed this item also bought") (Lee and Hosanagar, 2019). When popularity is the foundation for creating lists, the differences in the number of items listed may be even more pronounced compared to lists created using a complex algorithm. As a result, bestseller lists are expected to have a stronger influence on product recommendations than collaborative filtering lists. This also implies that there is lower product diversity in the CF recommendations since a smaller group of items dominates the distribution.

3.1.3 Exploring the heterogeneity of brands

Brands differ in terms of disposition across an online store, which can make some appear more in recommendations than others. In limited-edition markets, brand image and trust play an especially big role for consumers in considering a purchase (Chae et al., 2020). Moreover, brands in this market have a distinctive aesthetic connected to the brand (Park et al., 2022). This could induce the recommendation algorithm to be favoring certain brands over others, due to item features strongly relating to the brand. As a result, the recommendation count is expected to vary across the disposition of brands. One big factor that plays a role in the disposition of brands in a store is the entire assortment size. Since product recommendations act as a ”network”, product characteristics influence the number of recommendations it attains (Oestreicher-Singer and Sundararajan, 2012). In this network, brands form strong connections with each other, which results in clusters of brands recommending each other. The total size of the brand on the platform is expected to be positively related to the count of recommendations. This means that large brands with a huge assortment of items attain more recommendations. The recommendation count is expected to be lower for brands with a luxury image compared to more popular brands in fashion resale. This is mainly expected since such high-end items are typically very niche, which in categories shows to have a lower exposure in product recommendations (Lee and Hosanagar, 2019).

4 Data

This chapter discusses the collection process of the data for this study, the sample selection, and the transformation process to get to the measurable variables outlined in the conceptual framework (Figure 1). Lastly, a model-free analysis is done to illustrate the relationships between the variables in an early stage.

4.1 Collection process

4.1.1 Data context

Platform and retrieval method

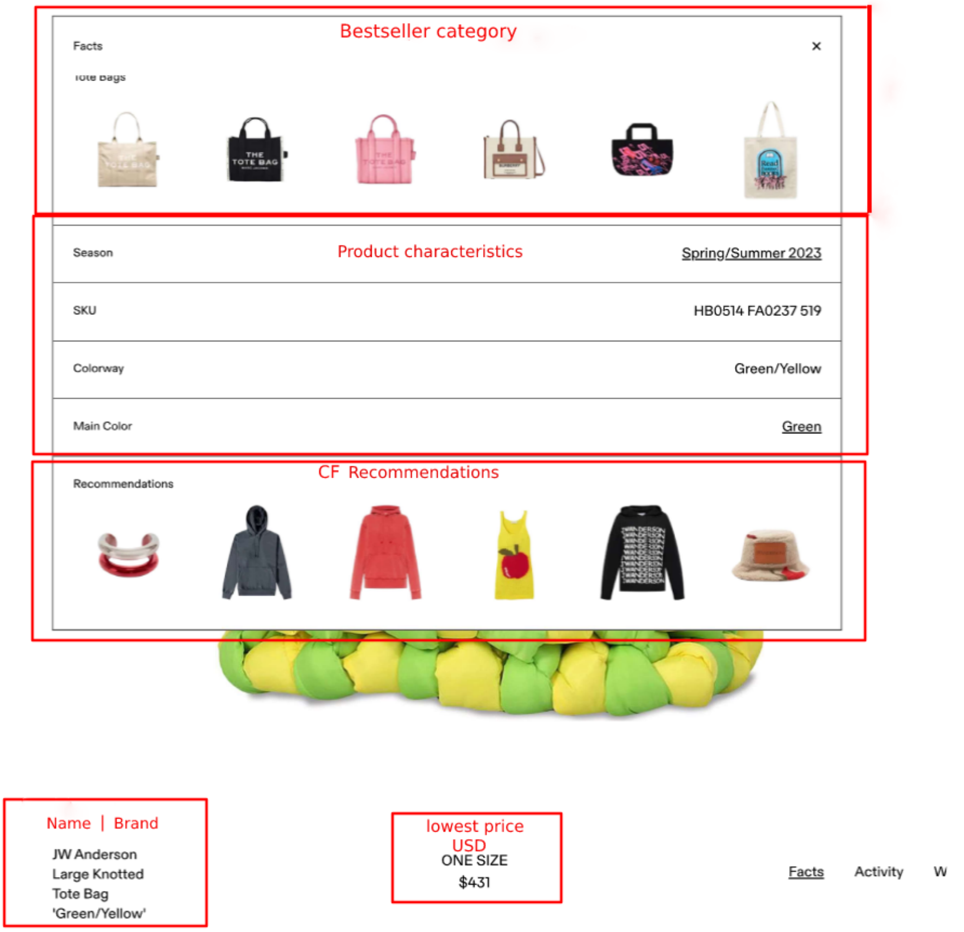
Data is gathered from *GOAT*, one of the most notable limited-edition fashion resale platforms with millions of unique monthly visitors (Similarweb, 2023). The platform is accessible globally, shipping rare products available to anyone willing to bid or pay for the listed price (GOAT, 2023). GOAT is one of the biggest and most recognized platforms in this growing industry, making it a valuable source for data retrieval to analyze the research objectives.

By accessing the API of Goat, data visible on the front end such as product characteristics were retrieved, as well as data not directly visible, such as the original retail price of a product or the assortment size per brand. The API endpoints were found by navigating the website and inspecting a specific page. In the "network" tab of the browser, multiple endpoints were found that corresponded to the content of the website displayed. For several of the endpoints, data could be obtained by using the request library of the Python programming language. For some endpoints, access through making direct requests was not possible. However, by utilizing a web driver and simply navigating to a specific endpoint, a list of data was visible and could be extracted by converting the data to a beautiful soup object. Since the data was structured in JSON format, this could be extracted consistently across all sampled products.

List types on GOAT

Out of the three lists, two are categorized as "trending items". The first list displays trending products that belong to the same brand as the product page, while the second list shows trending products within the specific category of the product (e.g. tops, trousers, etc.).

Figure 2: Different recommendation list types and product characteristics on GOAT



It is noteworthy that these lists remain constant across pages with the same brand or product category. The trending lists align with the bestseller lists discussed by Li et al. (2021), as they are likely to be selected based on the number of sales they receive. Therefore, we can consider these two lists as representing the bestseller list type in our study (Figure 1). It seems that the third list is generated by a more intricate algorithm, which not only presents similar-looking products to the central item but also dissimilar ones. This implies that the algorithm used is probably a combination of item-to-item-based collaborative filtering and content-based filtering methods. There are neither prices nor reviews of the recommendations visible.

Checking for personalization

Since the literature showed the relevance of personalization in the context of the study, it was checked whether GOAT used personalization for product recommendations. For the CF list, the products come from a single endpoint in the API per focal ID with no mention of personalization, which shows support these recommendations are the same across all users. For the two bestseller list types, there is some possibility of personalization. As could be found in the endpoint metadata of the API (see Appendix A). This metadata also shows that recommendations are based on ”relevance”, which could point to relevance based on a specific user profile. However, upon logging in on the website, and clicking and saving various items in the user profile, no changes occurred within the content between any of the lists between multiple sessions. This points to that personalization is either very subtle or only applied after a user's first purchase (which was not checked). As a final check for personalization, multiple browsers were checked across computers, mobile browsers, or the mobile app from GOAT. All showed the same content, proving that the lists show the same across users, at least until they haven't made their first purchase.

4.1.2 Sample selection

Relevant product endpoint

Product data was retrieved from live data by sampling 2,000 focal product pages in the sneaker and apparel categories from the platform. The sample was drawn from the endpoint corresponding to the ”popular” search filter of the website, which extended to 10,000 products for both the sneaker and apparel categories and was done by a one-time extraction. Knowing there are around 300,000 products in total on the platform, the population of 20,000 products might seem biased. However, upon an exploration of the data, it became clear that drawing a completely random sample outside the ”popular” section would have many recommended products with missing data. Therefore, the decision of drawing a random sample of 2,000 products within the 20,000 most popular products seemed most viable. Directly after the focal product pages were collected, the found product IDs were used as input for two more endpoints. Ideally, an even larger sample would be used. However, the script used to extract the data could only handle one extraction at a time. With a larger timespan, other factors could affect the featured product recommendations. Brands of product pages were included in the sample only when they have a minimum of 200 products on the platform, this again was done for the reason of saving time iterating through pages. In the analysis, this same selection of brands is used.

Specific product pages endpoint

The next step in the collection process was collecting the featured recommendations per product and across the different recommendation list types. For each of these found product recommendations, data had to be parsed back to the endpoint to retrieve the product characteristics such as the name, brand, and other variables described in Table 1. The extraction of the product recommendations had a timespan of around an hour.

Recent purchases endpoint

After all the product recommendations and the respective characteristics were collected, one more endpoint was contacted that contained the recent purchase history for each unique product. This is a list of the 20 most recent purchases of an item including the timestamp the purchase was made. For every product, up to 90 days of historical sales could be retrieved (or whenever the 20th sale happened in the past 90 days), which are later used to calculate the daily product revenue (see Figure 1).

Assortment size per brand endpoint

A summary of the assortment per brand could easily be obtained by an endpoint that contained data about the count of brands per listed brand. This is later used to represent the assortment size variable.

4.2 Data transformation

Table 1: Description of information gathered for each focal product and recommended product

Variable	Description
ID	Unique identifier per product across GOAT platform
Name	Official name of the product
Brand	Brand name of the product
Main category	Apparel or sneaker category
Silhouette	Specific category per brand for a sneaker with a similar design
Size	The obtained size per product ID
Product condition	The obtained condition (new no defects, new with defects, used) per size and product ID
Last sold USD	The last sold price per size, per product ID, and product condition
Lowest price USD	The lowest ask from a seller per size, per product ID, and product condition
Offer USD	The highest offer of a buyer per size, per product ID, and product condition
Instant ship USD[a]	The current price for instant shipping per size and per product ID

[a] *GOAT verifies products, instant shipping product means that verification is already done and the order is received faster.*

Table 2: Raw summary statistics of product recommendations

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
ID	154543	5180.226	2839.794	1	2804	7690	10300
Size	154524	15.139	22.472	1	7	12	200
Retail price USD	122034	176.748	192.122	23	110	190	8400
Lowest price USD	135454	261.564	272.035	16	131	291	16250
Last sold USD	99870	260.244	622.722	8	114	270	50000
Offer USD	33807	219.596	369.781	10	99	225	11000
Instant ship USD	43481	339.366	703.592	29	151	331	43205

Table 3: Raw summary statistics of recent purchase information per product ID

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Last sold USD	32403	210.908	335.252	11	17	23	20339
Size	32403	16.671	21.844	11.084	3	223.985	72
Purchase time	32403	2023-04-18 13:52:09	24 (days)	2023-02-09 18:24:03	2023-03-16 01:13:06	2023-05-01 00:12:43	2023-05-11 07:44:25

Cleaning and merge

The raw data collected consisted of the collected product recommendations with characteristics, the recent purchase data, and the assortment size data. Most of the cleaning took place in the data frame with the product recommendations. There are typically 8 recommendations present per list on the product page of GOAT, and three types of lists as explained in the first subsection of this chapter (also described in Table 1). Some products are unique in terms of category and therefore have fewer items than 8 in these lists. But generally, each list had 8, meaning that each focal product sampled has around 24 product recommendations, and the total recommendations present amounted to 47,373. Due to the wide variety in sizes per product, as well as different product conditions (new with no defects, used, etc.) the raw data consists of far more unique observations. Upon inspection of the data, it became clear that most products were sold as new with no defects. Since the products of other conditions, although interesting, played no further role in this research, they were left out before the aggregation process. There are some false values present in the raw data including a high retail price of $1,839,212, which upon inspection was erroneous output from the API. A quick search on *Stockx.com* shows the actual retail price is $220, hence it was replaced. Unreasonably high asks in the Lowest price USD value (corresponding to the lowest asking price from sellers), were listed as NA when over $2,000 unless the other sales values attained values above this threshold. The reason is that sellers can list any amount they desire, but likely no one actually purchases it for this price. Therefore, offer, last sold, and instant ship represent the current value of the product in a better way. Values having 0 for the pricing data also were named NA. Some size values had a minus sign (e.g.-14.5), which on further inspection was just size 14.5. These were therefore made a positive value. For the recently sold items, these adjustments were also made to the size values, as well as transforming the extracted values in cents to whole dollar values. After the operationalization process described in the next chapter, the two data frames could be merged by product recommendation ID. The data retrieved indicating the assortment size per brand did not need cleaning and could be merged directly with the other two data frames.

Operationalization of variables

Table 4: Operational Definitions of Variables

Variable Descriptions	
Variables first stage model	
Product revenue ($)	The revenue was obtained by extracting the last 20 sales for each product and taking the sum of prices sold divided by the period of the sales. For example, product ID 10834 has had 20 sales over the past 10 days with a total revenue of $2000. The product revenue is $200 The daily revenue can be expressed as: $\frac{\text{sum of revenues}}{\text{amount of days}}$
Recommendation count	The Recommendation count was calculated as the count of product recommendations across all sampled pages and the types of recommendation lists.
Brand	The brand the recommended product is part of.
List type	There are three list types present on GOAT: The ”CF recommendation list”, displays recommendations of items based on collaborative filtering. The ”Bestseller brand list” shows trending items for the respective brand, and a ”Bestseller category list” shows trending items for the respective category of the product.
Sneaker product	A dummy variable takes on 1 when the product is a sneaker and 0 when the product is an apparel item.
Variables second stage model	
η_b	The individual brand intercept that was extracted from the first model.
Assortment size	The assortment size is defined as the number of unique products per brand.
Luxury brand	The luxury brand dummy is assigned to items that have an explicit luxury aesthetic. Based on Vogue's runway list of brands (Nast, 2023).[a]

[a] *See Appendix B for the full list of luxury brands.*

Once the data were cleaned, the next step was aggregating it to fit the constructs of the conceptual framework (figure 1). The unit of analysis is a product found in a recommendation list. This means that every row in the final dataset should represent a recommendation, matched by a column of recommendation count. The recommendation count was obtained by grouping the 39,467 product recommendations after removing missing values, by their unique ID and the list they occurred. The list types in the data frame are separate columns and represent the proportions of how often a recommendation occurs in each list per ID.

Transforming the variable *Product revenue* was done by utilizing the recently sold data, and using the price data per product size. Unlike only retrieving one last sold price from the other endpoint, this data consists of the 20 most recent purchases with precise timestamps ranging up to 90 days back, or up until when the 20th sale in the past occurred. There is extreme variety in the number of sales made across the products; some popular items attain 20 sales in a few hours, while others have made almost no sales at all in the past 90 days. 2,836 IDs of the recommendations found, made no sales in this timeframe. To calculate the product revenue for the items with 20 items sold over a timespan between 1 day and 90 days, all sales were summed and divided by the time between the time of extraction and the first sale. For items with over 20 sales in one day, the total revenues of the 20 sales were also divided by the number of days. Since some products reached this mark in a matter of hours, the revenues are typically very high for these items. For IDs that have not made a single sale in the 90-day timeframe, the pricing data with no defined timestamps are used. Specifically, across all last sold prices of each size unit, the average is taken and formed into a new variable *average last sold*. If the last sold price is not available for a given size, the current highest offer data is used instead, if this data is also not available, the highest asking price is used to calculate the average. Since there is no time indication whatsoever on the last purchase, the assumption is made that at least one sale is made within the past 90 days. This assumes that each product generates at least a little daily revenue. The distribution mimics a long tail of items with low revenues, similar to what Oestreicher-Singer et al. (2013) describe in calculating revenues for book sales.

4.3 Model-free analysis

This subchapter presents the first results of the final dataset before fitting them into a regression model. The model-free analysis shows evidence of the relationships outlined in Chapter 3.

Table 5: Descriptive statistics recommendation list types

Measure	Recommendation list type		
	Bestseller brand	**Bestseller category**	**CF recommendation**
Recommendation count[a]	25.50	5.31	2.61
Product revenue $	9,230.11	4,826.31	2,844.35
Brand count	88	33	96
Share of luxury brand	0.08	0.00	0.11

[a] *Mean value for Recommendation count and Product revenue per product ID.*

Recommendation count

Figure 3: log-scaled recommendation count and product revenue

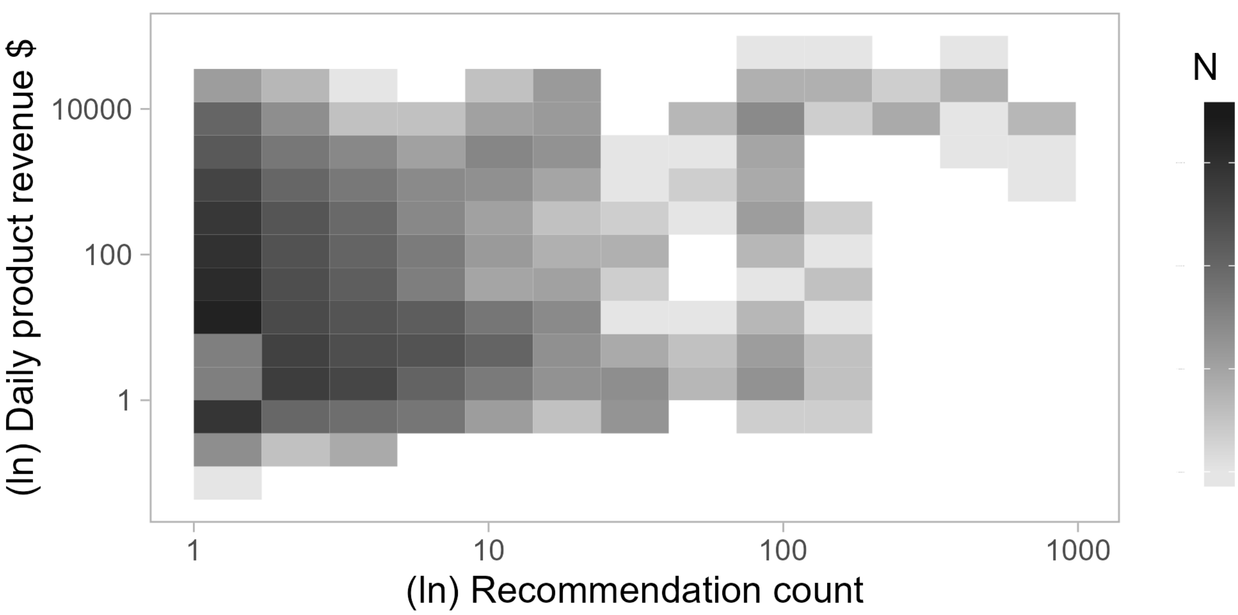


Figure 3 displays the relationship between daily product revenue and recommendation count, where N displayed in the legend is the degree of unique products that attain product recommendations across GOAT. The figure shows that most of the products are concentrated in the lower left corner of the graph, indicating that a lot of observed product recommendations are both low in product revenue and total count they occur in recommendations across GOAT. This is positive from a product diversity perspective, as this illustrates that various products are being recommended. However, there is also evidence that a select group of items attains a staggering amount of product recommendations. As this is primarily present in the upper right corner, it is the first evidence of a relationship between the product revenue generates and its recommendation count attained.

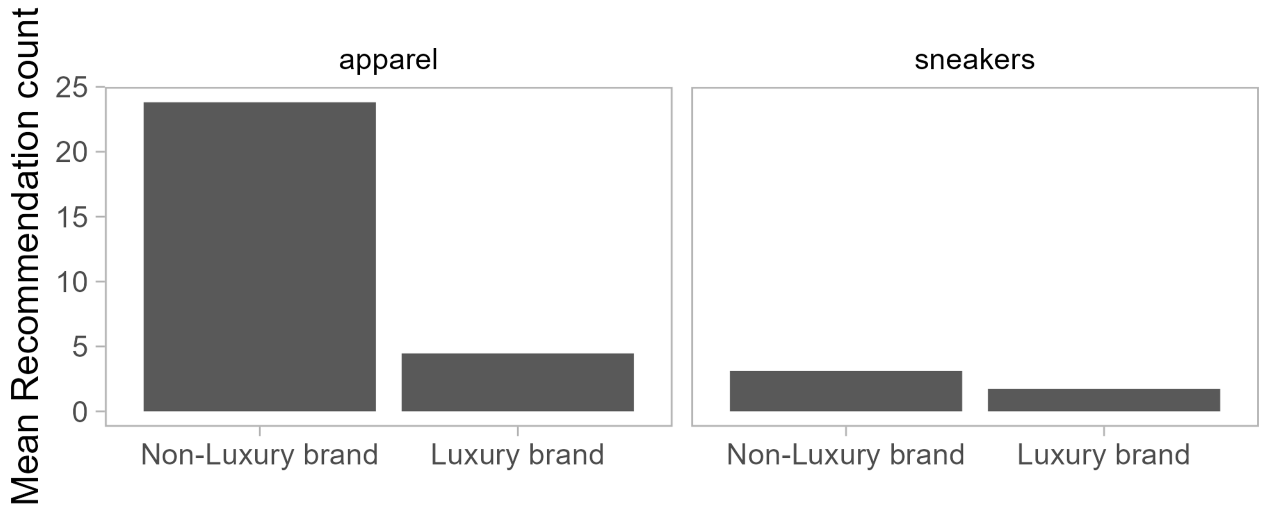
Figure 4: log-scaled recommendation count and product revenue (per list type)

Figure 4 shows the recommendation count across the three different list types that can suggest a product. There is a crucial difference between the bestseller list types and the collaborative filtering list types, as the former two list types clearly show concentration in the upper right corner. This indicates that a bestseller list, which is based on the ranking of most sold products, is less diverse in product recommendations. This logically follows from the fact that the same list of items is displayed across product pages with the same brand, this principle also applies to the bestseller category list.

The difference in recommendation luxury and non-luxury brand

The bar plots in Figure 5 show the differences between the two main categories of product types: ”sneaker” and ”apparel”, and the mean value of product recommendation count between a luxury and non-luxury brand. There is a pronounced difference in the mean count in both bar charts. This indicates that these niche types of luxury brands attain fewer recommendations, especially in the case the product the brand offers is an apparel item.

Figure 5: Relation luxury items and mean recommendation count



5 Model

5.1 First-stage model

In order to examine the relationships depicted in Figure 1, a log-log regression analysis is conducted at the product level. The analysis includes the moderating effects of the list type in which a product is featured. The decision to use a log transformation on both sides of the equation can be primarily motivated by the need to improve the model fit. Specifically, due to the presence of skewness in the recommendation count of products, a log transformation is applied to enhance interpretability. Similarly, a log transformation is also applied to the revenue generated by each product to account for the skewed distribution of demand (Oestreicher-Singer et al., 2013).

This model's equation is:

$$\begin{aligned} \ln(\mathrm{Y}_i) = \beta_0 + \beta_1 \ln(\text{product revenue}_i) \\ +\beta_2\text{cf recommendation list}_i + \beta_3\text{bestseller brand list}_i \\ +\beta_4\text{bestseller category list}_i \\ +\beta_5[\text{cf recommendation list}_i * \ln(\text{product revenue}_i)] \\ +\beta_6[\text{bestseller brand list}_i * \ln(\text{product revenue}_i)] \\ +\beta_7[\text{bestseller category list}_i * \ln(\text{product revenue}_i)] \\ +\beta_{8_b}\text{brand}_b + \beta_9\text{sneaker product}_i + \epsilon_i \end{aligned} \tag{1}$$

In the model the recommendation count (Y) per product i is the outcome. The predictor variables include the natural logarithm of the product revenue, depicted as β_1. The collaborative filtering list type and the bestseller list types for brand and category are included as β_2, β_3, and β_4 respectively. Separate beta's for interactions between these list types and the natural logarithm of the product revenue are included in the model as well. The variable $brand_b$ depicts a dummy variable that takes on the brand of each product i. To control for the effect of a product being part of one of the two main categories "apparel" or "sneakers", β_9 represents a single dummy variable for when product i is a recommendation of a sneaker. Finally, ϵ_i is the error term representing unexplained variability.

5.2 Second-stage model

The first-stage model does not account for the interaction of brand characteristics on the relationship between product revenue and recommendation count, which is the only theoretical and expected relationship of Figure 1 yet to be examined. The second model in this study aims to find an explanation for different expected effects between brands. Specifically, the explanation as to why some brands have a lower or higher recommendation count than others, controlling for all the other variables included in the first model. In this second model, individual brand intercepts of $brand_b$ are extracted and estimated based on the assortment size, and whether the brand is a luxury item or not. The dependent variable thereby takes on the coefficient value found in model 1. The variable operationalization of the predictor variables is found in Table 4. The method qualifies in this study since variables in this second stage are used as an instrument, and don't directly impact the outcome variable of recommendation count in the first-stage model (Angrist and Imbens, 1995).

This model's equation is:

$$\eta_b = \delta_0 + \delta_1 \ln(\text{Assortment size}_b) + \delta_2(\text{Luxury brand}_b) + \epsilon_b \tag{2}$$

Here η_b represents the extracted brand intercept from the first-stage model. Variables δ_1 and δ_2 represent the effects of assortment size and luxury brand, respectively. The error term is denoted by ϵ_b.

6 Results

In this chapter, the regression models are examined in three subchapters. Firstly, the fit of the first-stage model is discussed, and its results are presented. Following this, the variations of the outcomes are discussed in two separate stages. The model fit of the second-stage model is briefly discussed in this last subchapter as well.

6.1 Assesing model fit

Multicollinearity

Before running the model, a check for multicollinearity is conducted by analyzing a correlation matrix. The findings reveal that the variables of list types overlapped with each other. There is a big negative correlation between the CF collaborative filtering list and the bestseller category lists, which can lead to bias in the results.

Table 6: Correlation matrix model coefficients

	Recommendation count	Product revenue	Bestseller brand list	Bestseller category list	CF recommendation list
Recommendation count	1.00	0.54	0.18	-0.10	0.00
Product revenue	0.54	1.00	0.07	-0.07	0.03
Bestseller brand list	0.18	0.07	1.00	-0.37	-0.18
Bestseller category list	-0.10	-0.07	-0.37	1.00	-0.85
CF recommendation list	0.00	0.03	-0.18	-0.85	1.00

To account for this multicollinearity issue, the category list type is removed from the model. Now the issue of the correlation of the list types is resolved.

Final model after removing category list variable:

$$
\begin{aligned}
\ln(Y_i) = \beta_0 + \beta_1 \ln(\text{product revenue}_i) \\
+\beta_2 \text{cf recommendation list}_i + \beta_3 \text{bestseller brand list}_i \\
+\beta_5[\text{cf recommendation list}_i * \ln(\text{product revenue}_i)] \\
+\beta_6[\text{bestseller brand list}_i * \ln(\text{product revenue}_i)] \\
+\beta_{8_b} \text{brand}_b + \beta_9 \text{sneaker product}_i + \epsilon_i
\end{aligned}
\tag{3}
$$

Here the category list β_4 and the interaction of the category list with product revenue β_7 are removed from the model to eliminate the collinearity issues. As a final check for multicollinearity, the variance inflation factors are checked. This examines to what extent each predictor variable is correlated in estimating the outcome variable of recommendation count. None of the values exceed the level of 10, suggesting that multicollinearity is not a strong concern in the analysis.

Table 7: Variance Inflation Factors (VIF)

	VIF
log(product revenue)	3.61
CF recommendation list	2.66
Bestseller brand list	3.40
Sneaker product	6.44
Log(product revenue): cf recommendation list	4.58
Log(product revenue): bestseller brand list	2.96

Explanatory power

The initial model that was built to analyze *recommendation count* demonstrates a strong ability to explain the recommendation count. This is reflected in an adjusted R^2 value of 0.58, which indicates that 58% of the variance in the response variable can be accounted for by the explanatory variables. A high adjusted R^2 value such as this suggests that the model is a good fit for the data, and shows that the model can accurately capture the relationships between the variables during the examination of them.

Table 8: Output first-stage model

	Dependent variable:
	log(recommendation count)
log(product revenue)	0.187^{***}
	(0.007)
cf recommendation list	0.064^{*}
	(0.030)
bestseller brand list	0.452^{***}
	(0.063)
sneaker product	-1.048^{***}
	(0.057)
log(product revenue): cf recommendation list	-0.168^{***}
	(0.009)
log(product revenue): bestseller brand list	0.236^{***}
	(0.016)
constant	0.514^{***}
	(0.149)
Observations	5,657
R^2	0.592
Adjusted R^2	0.584
Residual Std. Error	0.635 (df = 5554)
F Statistic	78.846^{***} (df = 102; 5554)
Note:	*p<0.05; **p<0.01; ***p<0.001

6.2 Results from the first stage model

Relation product revenue and recommendation count

In order to answer whether there is a relationship between a product's revenue and its recommendation count, the coefficients of the log(product revenue) can be analyzed. The results indicate a significant and positive outcome with a β value of 0.187 and a p-value less than 0.001 (β = 0.187, $p < 0.001$). Due to the logarithmic transformation, the interpretation is that a one percent increase in revenue corresponds to a 0.19% increase in recommendation count for a product while holding all other variables constant. Table 8 provides the complete model output. This finding so far supports the relationship for the product recommendation algorithm's tendency to list items that obtain a higher product revenue more frequently. Moreover, the fact that a product is already recommended could boost the revenue even more, which is also captured by this relationship. As a result, customers that navigate the product pages encounter the same products in product recommendations, which are related to high product revenue.

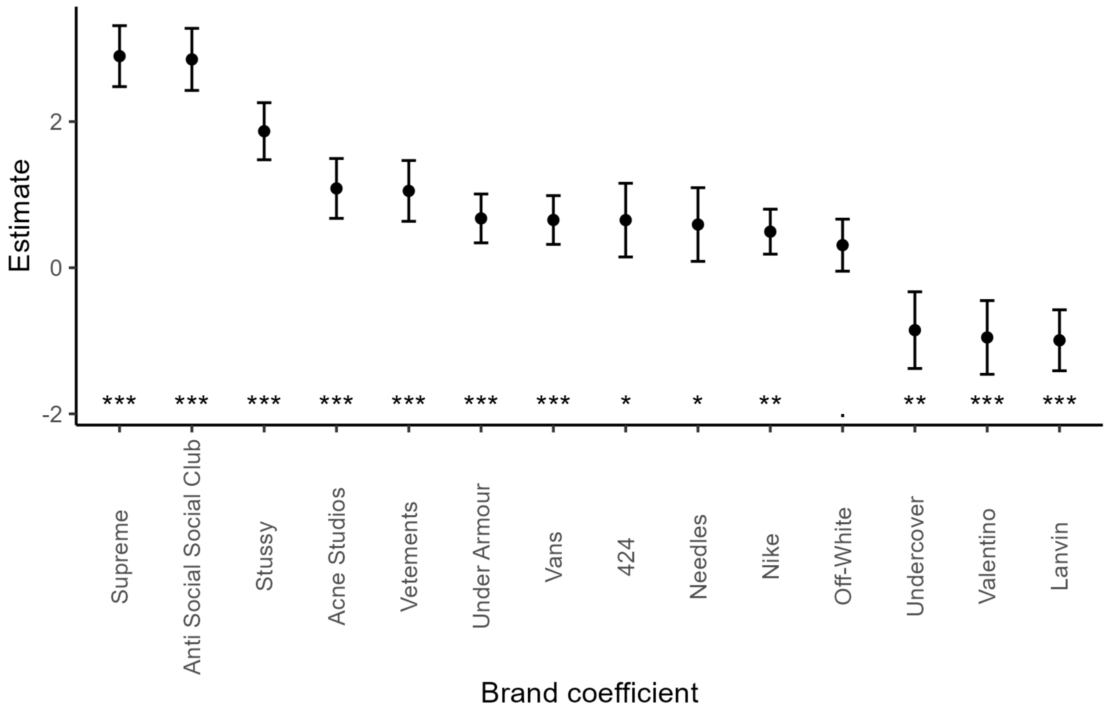
Moderating effect of the list type

List types are included in the model to indicate differences between them. To find an explanation of how much the main effect depends on the type of list (bestseller or collaborative filtering), the interaction terms of these lists with the log(product revenue) can also be interpreted. The recommendation list shows to be significant with a positive value (β = 0.064, $p = 0.032$). The interaction with product revenue, in contrast, is significant with a negative value (β = -0.168, $p < 0.001$). There seems no popularity bias present for this list, which was expected in Chapter 3. This could be due to the data only containing items that had at least one recommendation and one sale, thereby not accounting for products with absolutely no recommendations. For the bestseller brand list, a greater effect occurs compared to the CF recommendation list, with a significant positive value on the recommendation count (β = 0.452, $p < 0.001$). This positive value points to a higher average recommendation count, compared to the CF recommendation list. The findings demonstrate that, in comparison to the collaborative filtering lists, the average count of products in this list is higher, which translates to a lower diversity of items. The interaction between the bestseller brand list and the product revenue is highly significant with a value of $\beta = 0.236$ ($p < 0.001$). This corresponds with a 0.24 % increase in recommendation count on average per percentage of revenue increase. The findings of the differences in list types are also largely consistent with the model-free analysis in Chapter 4, where the concentration of products that attain both high revenues and are most often recommended was more prevalent in the brand list. Customers therefore more often see the same items in this list compared to the other two lists. Finally, the control variable for the product type (sneaker or apparel) shows a negative significant value ($\beta = -1.048$, $p < 0.001$). This again, like the different list types, indicates that the average count of products is lower on average, therefore the recommendations of this product type are more of the same items and customers might be likelier to encounter the same products in this item group, compared to a larger variety of sneakers in the recommendations.

Difference between brands

The expectation about brands as described in Chapter 3 is that due to their disposition such as size, and strong importance to users in looking for a product, the presence in product recommendations can change. As can be seen from the plot in Figure 6, there is a noticeable difference between the brands and their effect on recommendation count. Out of the 96 brands included in the model, 63 show a significant outcome ($p < 0.05$) on the recommendation count, keeping all the other variables in the model constant. This shows in brands such as Supreme ($\beta = 2.896$, $p < 0.001$), compared to Valentino ($\beta = -0.954$, $p < 0.001$). This confirms there is a difference in the exposure of certain brands over others in product recommendations as expected in Chapter 3.

Figure 6: Differences in recommendation count between a random selection of 14 brands



6.3 Results from the second stage model

In the second stage of the analysis, the individual brand intercepts among 63 brands are estimated. These brands were selected based on significant ($p < 0.05$) outcomes from the main model and were included in the analysis to explain the size of the intercept. The model has an adjusted R^2 of 0.17 which points to a moderate explanation of the variation of the brand intercepts. The expectations in Chapter 3 state that other variables not included in the first model can explain the variation. The assortment size indicates how many products of the brand are listed on the platform in total. The outcomes (see Table 9) support that the size of a brand's assortment has an impact on how much it is displayed across recommendations. Specifically, the assortment size has a positive and significant effect on the coefficient (δ = 0.269, $p = 0.002$), indicating that as the number of products on GOAT increases, the presence of recommendations becomes bigger as well.

Table 9: Assortment size and luxury brand effect on recommendation count

	Dependent variable:
	coefficient
log(assortment size)	0.269^{**}
	(0.085)
luxury brand	-0.355
	(0.247)
constant	-1.323^{*}
	(0.633)
Observations	63
R^2	0.198
Adjusted R^2	0.171
Residual Std. Error	0.914 (df = 60)
F Statistic	7.385^{**} (df = 2; 60)
Note:	$^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

The dummy variable for a luxury product showcases a negative effect, though insignificant (δ = -0.355, p = 0.157). This suggests that luxury products might be less likely to be recommended compared to non-luxury products since there is less exposure through product recommendations than more mainstream brands. This would be consistent with the expectation of niche items being recommended fewer times due to the overshadowing of mainstream brands that are more favored by the algorithm in product recommendation lists. Because the value is not significant, this can however not be confirmed. The insignificant value could be because the sample included only brands with above 200 products. Brands with even a smaller assortment on the platform might show more negative values for luxury products.

7 Discussion

7.1 Conclusions

This thesis illustrated what factors influence product recommendations in the growing limited-edition fashion resale industry. Firstly, it shows that the amount of recommendations a product receives is related to the revenue it attains, which supports previous research done in e-commerce and product recommendation research. Secondly, it establishes that there is a difference between a bestseller list and a list based on collaborative filtering in attaining recommendation count. Specifically, curated bestseller items representing the brand of the product tend to have a greater number of recommendations per product than categorical or CF recommendation lists. Additionally, the model-free analysis shows that in bestseller lists, the recommendation count is attained by a small group of items, while CF lists are more widely distributed. Suggesting that these trending lists for brands and categories have less diversity compared to collaborative filtering. Thirdly, it was found there are noticeable differences in the amount brands show up in product recommendations, which is affected by the assortment size of such brands, but not necessarily whether the brand can be considered a luxury or mainstream. A product of a brand with a big assortment on average attains more product recommendations. For products that have a brand with a luxury appeal, the average recommendation count is not confirmed to be lower compared to a mainstream brand.

7.2 Theoretical contribution and managerial implications

The findings on the relationship between product revenue and recommendation count, hugely support the findings of previous studies done on Amazon (Oestreicher-Singer et al., 2013). The second theoretical contribution is that this is one of the first studies comparing a bestseller recommendation list with a collaborative filtering list and showing significant differences (Li et al., 2021). Lastly, the findings on differences in brand characteristics impacting the relationship between product revenue and recommendation count, complement previous research that some item features as genres can dominate over others (Lee and Hosanagar, 2014, 2019). Although not a significant finding, this study shows that mainstream products could potentially be recommended more across product pages compared to niche luxury brands.

The findings complement a wider stream of research on digital store presentation, that illustrates how important browsing and discovery are for hedonic products such as limited-edition items (Li et al., 2020). The differences found between the bestseller and collaborative filtering present more insight for managers into the tradeoff made for offering popular items with high product revenue and items that are hardly sold and don't get recommended. Managers can run online experiments and analyze clickstream data on how users react to adding or removing a bestseller list, compared to a list based on collaborative filtering. By analyzing the product behavior of users through clicks and purchases in these conditions, consideration can be made of how much emphasis should be put on product discovery in recommendation lists. Personalization is likely an important factor in offering a wider variety of items. Based on the findings, it is advised to managers to personalize product recommendations for specific brands to users, such that important aspects such as underexposure of small and niche brands are not ignored by customers that find these brands relevant.

7.3 Limitations and future research

One major limitation of this study is the selection of items. All observations in the sample had at least one recommendation through another product, which might leave out a big part of items that never have gotten a product recommendation at all. This might bias collaborative filtering lists especially, as there are numerous items with both no sales or a recommendation on the platform. Hence, the interaction with product revenue is likely higher than found in this study. Potentially time series data could add valuable insights into how various changes over time. As fashion is a rapid market, trends play a big role in what consumers want, and changes in product recommendations might reflect this. Another limitation compared to studies advised in the literature is that no actual data could be collected on the conversion of recommendations on sales. Since different items can have a different effect on the actual clicks and purchase of an item, this is a vital aspect that can yet be considered. Lastly, since this study was conducted in a specific set of recommendation systems, it does not generalize as well to all platforms within the industry of limited-edition resale. Since different platforms have different lists of recommendation algorithms as well as different customer segments they focus on, their findings in product recommendations might differ from this study.

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Appendix A: Metadata GOAT


```
request:
  page:                                  1
  num_results_per_page:                  24
  sort_by:                               "relevance"
  sort_order:                            "descending"
  term:                                  ""
  fmt_options:                           {…}
  section:                               "Products"
  features:
    query_items:                         true
    a_a_test:                            false
    auto_generated_refined_query_rules:  true
    manual_searchandizing:               true
    personalization:                     true
    filter_items:                        true
    use_reranker_service_for_search:     false
    use_reranker_service_for_browse:     false
    use_reranker_service_for_all:        false
    custom_autosuggest_ui:               false
  feature_variants:
    query_items:                         "goat_weighted_ctr_w_atc_purchases_diff_periods"
    a_a_test:                            null
    auto_generated_refined_query_rules:  "soft_rules"
    manual_searchandizing:               null
    personalization:                     "default_personalization"
    filter_items:                        "goat_weighted_ctr_w_atc_purchases_diff_periods"
    use_reranker_service_for_search:     null
    use_reranker_service_for_browse:     null
    use_reranker_service_for_all:        null
    custom_autosuggest_ui:               null
  searchandized_items:                   {}
  browse_filter_name:                    "group_id"
  browse_filter_value:                   "all"
```

Appendix B: Luxury brands

1. Alexander McQueen
2. Amiri
3. Balenciaga
4. Bottega Veneta
5. Dior
6. Givenchy
7. Gucci
8. Rick Owens
9. Saint Laurent
10. Versace
11. Stone Island
12. Maison Margiela
13. Burberry
14. Jacquemus
15. Raf Simons
16. Vetements
17. MM6 Maison Margiela
18. Marni
19. Casablanca
20. Christian Louboutin
21. Loewe

22. Valentino

23. Moncler

24. Fendi

25. 3.PARADIS

26. A-Cold-Wall*

27. Acne Studios

28. C2H4

29. Charles Jeffrey Loverboy

30. Courrèges

31. Dior

32. Enfants Riches Déprimés

33. Helmut Lang

34. Issey Miyake

35. Jacquemus

36. Junya Watanabe

37. Kenzo

38. Lanvin

39. Louis Vuitton

40. Martine Rose

41. Off-White

42. Ottolinger

43. Paco Rabanne

44. Polo Ralph Lauren

45. Rick Owens DRKSHDW

46. Comme des Garçons

47. Tao Comme des Garçons

48. Undercover

49. We11done

50. Yohji Yamamoto Pour Hommee

51. Fear of God

Appendix C: Analysis output

Output first-stage model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.5143	0.1486	3.46	0.0005
log(product_revenue)	0.1874	0.0071	26.45	0.0000
cf_recommendation_list	0.0640	0.0299	2.14	0.0326
bestseller_brand	0.4521	0.0627	7.21	0.0000
brand424	0.6518	0.2574	2.53	0.0113
brandA-Cold-Wall*	-0.7175	0.2062	-3.48	0.0005
brandAcne Studios	1.0853	0.2090	5.19	0.0000
brandadidas	0.5363	0.1582	3.39	0.0007
brandAir Jordan	0.7985	0.1569	5.09	0.0000
brandAlexander McQueen	-0.0156	0.1926	-0.08	0.9356
brandAmbush	0.2520	0.2239	1.13	0.2604
brandAmi	0.1443	0.2407	0.60	0.5490
brandAmiri	0.6385	0.1801	3.54	0.0004
brandAnti Social Social Club	2.8516	0.2168	13.15	0.0000
brandAries	-0.3331	0.2408	-1.38	0.1668
brandASICS	0.5425	0.1630	3.33	0.0009
brandBalenciaga	0.6625	0.1841	3.60	0.0003
brandBalmain	0.2578	0.2203	1.17	0.2420
brandBAPE	0.8194	0.1745	4.70	0.0000
brandBillionaire Boys Club	2.2840	0.2345	9.74	0.0000
brandBottega Veneta	0.0349	0.2288	0.15	0.8788
brandBrain Dead	0.9872	0.2201	4.49	0.0000
brandBrooks	0.4602	0.3988	1.15	0.2485
brandBurberry	0.4148	0.1971	2.10	0.0354
brandCarhartt WIP	0.6006	0.2239	2.68	0.0073
brandCasablanca	0.6017	0.2289	2.63	0.0086
brandChampion	0.4808	0.6544	0.73	0.4626
brandChristian Louboutin	0.4283	0.6543	0.65	0.5128

brandChrome Hearts	0.1111	0.2038	0.54	0.5858
brandComme des Garçons	-0.9678	0.2409	-4.02	0.0001
brandComme des Garçons PLAY	0.8486	0.1863	4.55	0.0000
brandConverse	0.7515	0.1668	4.51	0.0000
brandCourrèges	0.3218	0.2062	1.56	0.1187
brandCrocs	-0.8260	0.2363	-3.50	0.0005
brandDiadora	0.5252	0.2002	2.62	0.0087
brandDime	0.2308	0.2411	0.96	0.3386
brandDior	-0.2807	0.2252	-1.25	0.2126
brandEwing	-0.2434	0.3051	-0.80	0.4249
brandFear of God	-1.0149	0.2409	-4.21	0.0000
brandFear of God Essentials	1.8122	0.1897	9.55	0.0000
brandFendi	0.4264	0.3987	1.07	0.2848
brandFila	0.4571	0.6543	0.70	0.4848
brandGallery Dept.	-0.3719	0.2248	-1.65	0.0981
brandGivenchy	1.0479	0.2092	5.01	0.0000
brandGolden Goose	0.5779	0.3540	1.63	0.1026
brandGucci	0.0673	0.1853	0.36	0.7164
brandHelmut Lang	-0.4012	0.3954	-1.01	0.3103
brandHeron Preston	1.3590	0.2240	6.07	0.0000
brandHoka One One	0.4304	0.2545	1.69	0.0908
brandHuman Made	0.7102	0.2483	2.86	0.0042
brandIcecream	0.9169	0.2484	3.69	0.0002
brandJacquemus	0.6434	0.2122	3.03	0.0024
brandJil Sander	-1.0263	0.2976	-3.45	0.0006
brandJust Don	-0.8896	0.2976	-2.99	0.0028
brandKapital	0.6802	0.2408	2.82	0.0048
brandKarhu	1.4481	0.2314	6.26	0.0000
brandKsubi	-0.2231	0.2241	-1.00	0.3196
brandLanvin	-0.9930	0.2128	-4.67	0.0000
brandLoewe	-0.0909	0.2157	-0.42	0.6733
brandLouis Vuitton	-2.6533	0.6531	-4.06	0.0000

brandMaison Margiela	0.5347	0.2679	2.00	0.0460
brandMarine Serre	0.9609	0.2090	4.60	0.0000
brandMarket	0.1099	0.2346	0.47	0.6396
brandMarni	0.6138	0.2036	3.01	0.0026
brandMizuno	0.7984	0.4757	1.68	0.0933
brandMM6 Maison Margiela	0.4691	0.1903	2.47	0.0137
brandMoncler	0.2276	0.2093	1.09	0.2769
brandMoncler Genius	-0.8512	0.2810	-3.03	0.0025
brandMusic	0.7920	0.3497	2.27	0.0235
brandNeedles	0.5913	0.2572	2.30	0.0216
brandNeighborhood	-0.8734	0.2573	-3.39	0.0007
brandNew Balance	0.7155	0.1594	4.49	0.0000
brandNike	0.4936	0.1570	3.14	0.0017
brandOff-White	0.3093	0.1817	1.70	0.0888
brandON	0.3521	0.1888	1.86	0.0623
brandOnitsuka Tiger	0.1239	0.2477	0.50	0.6169
brandPleasures	-0.9707	0.2243	-4.33	0.0000
brandPolo Ralph Lauren	0.3365	0.2410	1.40	0.1626
brandPuma	0.6942	0.1629	4.26	0.0000
brandRaf Simons	0.8486	0.2206	3.85	0.0001
brandReebok	0.6027	0.1664	3.62	0.0003
brandRhude	1.5101	0.2198	6.87	0.0000
brandRick Owens	0.8033	0.1921	4.18	0.0000
brandSaint Laurent	0.5918	0.1960	3.02	0.0025
brandSaint Michael	1.0998	0.2344	4.69	0.0000
brandSalomon	-0.7108	0.2318	-3.07	0.0022
brandSaucony	0.9873	0.1776	5.56	0.0000
brandSports	-0.0087	0.2246	-0.04	0.9690
brandStone Island	0.5591	0.2160	2.59	0.0097
brandStussy	1.8684	0.1992	9.38	0.0000
brandSupreme	2.8961	0.2129	13.60	0.0000
brandThe North Face	-0.6362	0.2346	-2.71	0.0067

brandTimberland	0.2566	0.2839	0.90	0.3661
brandUnder Armour	0.6750	0.1706	3.96	0.0001
brandUndercover	-0.8541	0.2678	-3.19	0.0014
brandValentino	-0.9540	0.2572	-3.71	0.0002
brandVans	0.6535	0.1701	3.84	0.0001
brandVersace	0.1857	0.1957	0.95	0.3427
brandVetements	1.0516	0.2122	4.96	0.0000
brandVisvim	-0.9234	0.2572	-3.59	0.0003
product_type_categorysneakers	-1.0477	0.0567	-18.49	0.0000
log(product_revenue):cf_recommendation_list	-0.1679	0.0089	-18.84	0.0000
log(product_revenue):bestseller_brand	0.2357	0.0164	14.38	0.0000

Output second-stage model

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-1.3235	0.6327	-2.09	0.0407
log(assortment_size)	0.2688	0.0847	3.17	0.0024
luxury_dummy	-0.3547	0.2474	-1.43	0.1569