Entrepreneurship in the Pre-Owned Clothing Market: The Role of Pictures in Second-Hand Marketplaces *

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Abstract

In today's visually-driven world, images have a powerful influence on consumer decisions, especially in the rapidly growing second-hand fashion market. This study investigates the role of pictures in shaping buyer behavior, focusing on whether the use of personal images by sellers—acting as micro-entrepreneurs—can significantly impact sales performance.

The fashion industry relies heavily on visual appeal—texture, fit, style, all of which can be instantly conveyed through a photograph. Sellers on peer-to-peer platforms are not just individuals; they function as entrepreneurs managing their own small businesses. They face an important question: should they feature themselves in product images to boost sales, even if it means giving up some privacy? This touches on the delicate balance between privacy concerns, effective marketing, and entrepreneurial decision-making.

We explore this question by analyzing the photos used in product listings, examining key factors like image quality, the type of subject (clothing alone, real person, or professional model), and the overall aesthetics of the photos. We assess how these elements influence listing prices, the likelihood of a sale, and the time it takes for a product to sell. Through regression analyses that also consider user experience, product reviews, and descriptions, we identify what truly drives success for these micro-entrepreneurs in a competitive marketplace.

Our findings suggest that while experience and reputation matter, the visual presentation of products remains crucial. This study demonstrates whether sacrificing a degree of privacy by featuring personal images can lead to higher prices or quicker sales, providing entrepreneurial sellers with valuable insights into leveraging visual appeal to enhance their business performance in a crowded market.

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1 Introduction

Second-hand online marketplaces have increase in popularity in the last decade. Such platforms let users buy and sell any kind of objects from books, furniture, electronics, but predominantly clothes. Online second-hand marketplaces like Vinted have grown considerably over the last years. For example, according to Statista (2024), Vinted went from a revenue of $ 10M in 2017 to almost $ 600M in 2023. .

In 2024, the online resale market is flourishing with a variety of platforms catering to different niches and preferences. *Poshmark* stands out with its social networking features, allowing users to follow favorite sellers and engage with a community-oriented marketplace for fashion, accessories, and home decor. *Depop* attracts a younger demographic, blending marketplace functionality with social media elements, making it a hub for trendy and unique fashion items. *Vestiaire Collective* focuses on luxury pre-owned fashion, ensuring authenticity through a meticulous verification process and promoting sustainable fashion practices globally. These platforms provide diverse options for consumers looking to buy or sell second-hand items, each offering unique features tailored to different segments of the market.

Consumer behavior in second-hand markets is influenced by various factors, including perceived value, environmental consciousness, and economic benefits. Henceforth, the consumer base on these platforms is heterogeneous, ranging from those who prioritize sustainability to avid deal hunters. Some companies emphasize their commitment to sustainability, appealing to eco-conscious consumers who seek to reduce waste and support a circular economy. Others focus more on the economic aspect, attracting buyers looking for cost-effective alternatives to new items. This diversity in consumer motivations reflects the broad appeal and varied marketing strategies of second-hand marketplaces.

The role of these platforms is to reduce information asymmetries between users in buying and selling. Most platforms have a reputational system with reviews and ratings (Filippas et al., 2022). Another way to build trust within the community, it is recommended to add a profile picture and a short bio. This personal touch helps other users feel more connected and confident in their interactions.[1].

As (Troncoso and Luo, 2023) analyzed, the use of a profile picture is not straightforward in building trust, with other platform design choices such as reputational systems and product recommendations also playing significant roles. They state that in online labor marketplaces for freelancers, "looking the part" and job fitness are crucial for securing employment.

In online products marketplaces, the context is similar, sharing the profile picture features, but it is very difficult to "look the part" as a seller. Moreover, in this setting, the same reasoning can be applied to every product, since, the best the product is looking, the easiest is to sell. Platforms, in fact, recommend several best practices. Sellers should ensure items are clean and "make them

[1]Source: Startup on tise.com

presentable.", such as using natural lighting for photographs accurately captures the item's true color and details, with multiple angles, including close-ups of unique features or flaws, should be provided. Additionally, they specifically suggest users to model or "try on" the clothing to help potential buyers better understand the fit and appearance. [2].

Perceptions of product fit are often formed holistically, taking into account multiple visual cues present in listing photos that extend beyond basic product information. Visual elements such as the cleanliness and presentation of an item significantly influence perceptions of its quality and desirability. For example, a meticulously arranged product photo can convey a sense of professionalism and care, suggesting that the item itself is of high quality. These perceptions, in turn, can affect how well a product fits specific needs, whether for formal occasions or casual wear. The context in which a product is presented plays a crucial role in shaping these perceptions.

Moreover, perceptions of product fit can be category-specific; the same product may be evaluated differently depending on the category under consideration. For instance, a "vintage-looking" item may be perceived as highly suitable for a retro fashion enthusiast but may be considered a poor fit for someone seeking modern, contemporary styles. This category-specific perception underscores the importance of understanding the target audience and tailoring product presentations accordingly to meet diverse consumer preferences.

In addition to these factors, the setting in which a product is presented further influences perceptions of fit. Products can be displayed in various ways, such as using standard store or stock photos, or presenting them in more informal and engaging settings. For example, showcasing a product within a room setup can help consumers visualize how it would look in their own space, while presenting it against a scenic landscape can evoke certain emotions and associations. For clothing items, displaying the product being worn by a model or lying gracefully on a surface can highlight different aspects of its design and functionality. Figure 1 illustrates some common product display methods used on various platforms, demonstrating how different presentation styles can impact consumer perceptions.

We could see user's as entrepreneurs that try to increase sales through their "ads", encompassing a diverse range of strategies and techniques aimed at enhancing product visibility and appeal. Effective advertising not only highlights the features and benefits of a product but also strategically leverages visual and contextual elements to align with the target audience's preferences and expectations.

Our research is motivated by observations indicating that consumers frequently rely on the presentation of products to assess their suitability in second-hand marketplaces. This judgment is influenced by whether the product is displayed in a professional setting, modeled by individuals, or shown in a homemade environment. The way items are photographed, including the use of models and the clarity of images, plays a crucial role in shaping consumer perceptions and

[2]Source: tise.com Guidelines

their subsequent purchasing decisions.

Research indicates that judgments based on appearance can have significant downstream effects on decision-making (Olivola and Todorov, 2010). In the context of second-hand marketplaces, the presentation of products can similarly influence consumer perceptions and purchasing decisions. For instance, products that are displayed in professional settings, modeled by individuals, or shown in clear, well-lit photographs often attract more buyers. To the best of our knowledge, however, no academic research has yet investigated the potential downstream consequences of appearance-based perceptions on purchasing decisions in online second-hand marketplaces.

In the marketing literature, (Luo et al., 2008) suggested that consumers often use both objective and subjective criteria to evaluate products. Similarly, we explore whether consumers in second-hand marketplaces use both arguably more objective criteria (e.g., product descriptions, seller ratings, and price) and arguably more subjective criteria (e.g., the presentation quality of the product, the setting of the photograph, and the inclusion of models) when deciding what to purchase.

For this reason, the seller must decide on the level of effort to invest when photographing the product for their listing. It can be seen as trivial by many, but the level of effort behind a product listing can make the difference by significantly impacting the product's perceived value and attractiveness to potential buyers.

To understand the impact of the picture in second-hand markets, I perform a large-scale observational study to answer the following research questions:

- **How does the effort shown in product listings influence pricing behavior?** This research question explores whether the level of effort invested in creating a product listing—such as the use of professional imagery, detailed descriptions, and a carefully structured presentation—impacts the seller's pricing strategy. Specifically, does a higher perceived effort lead sellers to price their products at a premium, based on the assumption that consumers interpret greater effort as a signal of higher quality or reliability?

- **How does the effort invested in product listings affect sales performance?** This question investigates the relationship between the effort put into a product listing and the resulting sales outcomes. Does the additional effort in enhancing listing quality—through better visuals, richer product information, and professional presentation—lead to higher conversion rates and greater sales success? By addressing this, the study aims to uncover whether a seller's investment in high-effort listings translates into improved market performance.

- **How does the effort expended in product listings impact the time to sell?** This research question seeks to determine whether increased effort in product presentation affects the time it takes to sell a product. Does a well-crafted, high-effort listing result in faster sales due to increased consumer trust and product desirability? Alternatively, does the potential for higher pricing in high-effort listings slow down the time-to-sale, as buyers deliberate over competing offers?

Our study is backed by data from tise.com the largest second-hand marketplace in Norway. We use data on more than 3M product listings, posted between the first day of January 2021 and the last day of December 2023.

We leverage modern computer vision techniques ti analyze the first picture of every product listing, the one visible on the "explore" page and the profile picture.

Our research makes significant contributions to the understanding of visual presentation in second-hand marketplaces.

Firstly, we extend the literature on the influence of images in online marketplaces (e.g., Pope and Sydnor (2011), Doleac and Stein (2013), Edelman et al. (2017),Ert et al. (2016), Athey et al. (2022),Troncoso and Luo (2023)) by demonstrating that product photos can impact purchasing decisions based on appearance-related perceptions, beyond established factors like product details or seller reputation. To our knowledge, this study is the first empirical investigation showcasing the critical role of product presentation in second-hand online marketplaces.

Secondly, we contribute to the body of work on online marketplace design and reputation systems (e.g., Sun (2012), Tadelis (2016), Watson et al. (2018), Luca (2017)) by exploring the dynamic interaction between image quality and reputational feedback. This study is among the first to reveal how the quality of product photos, combined with reputation systems, influences consumer trust and purchasing behavior.

Thirdly, we build on the work of (Ma et al., 2019) which explores the impact of image quality on purchasing behavior in peer-to-peer marketplaces. Their findings highlight that higher quality images are associated with increased sales and enhanced perceived trustworthiness, although other factors like view count also play a significant role.

2 Data

This study utilizes data from `tise.com`, a prominent second-hand fashion platform primarily serving the Nordic region, including Norway, Sweden, Denmark, and Finland. Tise facilitates the buying and selling of pre-owned fashion items by integrating various features designed to enhance user experience and ensure transaction safety. Key functionalities of the platform include an integrated payment solution that secures transactions, a robust search system allowing users to filter by specific categories and brands, and opportunities for users to generate additional income through reselling.

A strong emphasis on sustainable shopping is central to Tise's mission, promoting the reuse and recycling of fashion items to support environmental conservation efforts. Users can upload photos of their items to list them for sale, while also accessing features that highlight the latest fashion trends. This dual focus not only aids users in staying updated with current styles but also encourages responsible consumer behavior through second-hand shopping.

The community aspect of Tise is significant, with millions of active users interacting within the platform to create a dynamic marketplace environment. This extensive user base drives economic activity and fosters a sense of community among second-hand fashion enthusiasts. The platform's design elements, such as reputational systems and product presentation features, play crucial roles in influencing purchasing decisions and building trust among users.

For the purposes of this analysis, the dataset is restricted to adult clothing apparel, excluding categories such as child and baby items, interior and furniture, outdoor gear, art and design, devices and audio, and leisure and hobbies. These excluded categories are retained solely for constructing metrics related to reputation and user experience within the marketplace.

2.1 Rationale for Selecting Tise Over Vinted

The primary reasons for choosing Tise over Vinted, the leading second-hand marketplace in Europe, are as follows:

1. **Single Market Structure:** Unlike Vinted, which allows users to trade across multiple markets, Tise operates as a single market within each Nordic country. This localized structure ensures that interactions occur solely within each country, providing a more cohesive and region-specific trading experience.

2. **Comprehensive User Purchase History:** Tise maintains a detailed history of user purchases, enabling thorough tracking of wardrobes and user experiences. This feature offers valuable data for analyzing consumer behavior and market trends within the platform.

3. **Flexibility in Photo Posting:** Tise permits the use of both stock and professional photos in product listings, unlike Vinted, which imposes restrictions. This policy allows for a complete overview of posting behavior, offering insights into how different presentation strategies impact consumer engagement and sales.

These factors make Tise a preferable choice for analyzing localized market dynamics, consumer behavior, and the impact of product presentation in second-hand marketplaces.

2.2 Data Collection

Data was collected from `tise.com` using their hidden API, resulting in over 10 million data points spanning four countries from January 2016 through March 2024, the date of data retrieval. To ensure a more focused and controlled analysis, the dataset was subsequently subset to include only data from female users from Norway. This approach mitigates confounding factors such as varying legislation, cultural customs, currency differences, and consumer behaviors across the Nordic countries. Norway, being the origin country of Tise with the highest platform usage rate, provides a rich and concentrated dataset for analysis. Additionally, the Norwegian market lacks significant competitors in the second-hand marketplace sector, making it an ideal environment to study the impact of Tise without external market influences.

After subsetting, the dataset comprises 3,048,284 observations across 22 categories. Each observation corresponds to an individual product listing. The data collected for each product includes variables such as category, condition, country of origin, reference gender, price, creation date, size, update date, brand, sold status, caption, colors, and likes count. At the user level, the dataset encompasses the entire wardrobe of each user, including the history of sold products, review counts, review texts, and average ratings.

2.3 Data Description

The data analyzed in this study reveals significant gender-based patterns in user demographics and product offerings within the marketplace. As illustrated in Figure 2, the majority of users are female (78%), while males constitute 10.2%. A similar percentage of users prefer not to disclose their gender, and a small minority (1.69%) identify as "Other". Correspondingly, product offerings are predominantly targeted towards females (82.5%), as shown in Figure 3. Products labeled for any gender account for 11.8%, and those intended for males represent 5.65%. These trends highlight the marketplace's strong orientation towards female users and products, suggesting potential implications for gender-specific marketing strategies.

Figure 4 presents a time series analysis of weekly product postings categorized by gender from 2016 to 2023. The data shows a pronounced and increasing prevalence of female-targeted products, especially from 2020 onward. In contrast, postings for male-oriented, gender-neutral ("Any"), and unspecified ("NA") categories have remained relatively stable and significantly lower. This trend underscores a strong gender skew in the marketplace, suggesting a higher focus on female-oriented products either due to demand or supply dynamics.

The platform has undergone significant changes over time, as evidenced by various aspects such as condition disclosure, brand disclosure, user reviews, and product condition distribution. Figure 9 provides a comprehensive overview of these trends. The graph on condition disclosure shows a steady increase in the percentage of products with disclosed conditions, indicating greater transparency (Figure 7). Similarly, brand disclosure has also increased, reflecting a shift towards more branded product listings (Figure 6). The review graph highlights the expansion of user-generated reviews over time, which plays a crucial role in enhancing trust and product credibility (Figure 5). Lastly, the product condition graph illustrates the evolving distribution of product conditions, with a noticeable increase in the proportion of new and lightly used items (Figure 8). Together, these trends suggest that the platform has matured into a more structured and transparent marketplace.

Statistic	Mean	Median	SD	Min	Max
Price	341.37	200.00	452.47	1.00	4999.00
Sold	0.63	1.00	0.48	0.00	1.00
Time to Sell (Days)	97.82	31.38	149.98	0.00	1170.84

Table 1: Descriptive Statistics

Variable	Mean	Median	SD	Min	Max
Reviews at Posting	13.89	5.00	26.33	0.00	894.00
Reviews at Purchase	18.01	8.00	30.43	0.00	1014.00
Average Review Value at Posting	7.40	9.00	3.18	1.00	9.00
Cumulative Posted	58.71	29.00	85.62	1.00	973.00
Cumulative Sold	45.32	20.00	73.29	0.00	953.00
Review to Sold Ratio	0.77	0.36	4.33	0.00	618.00
Like Count	8.11	4.00	16.08	0.00	1658.00
Image Count	2.79	3.00	1.16	1.00	9.00

Table 2: Descriptive Statistics for Numerical Variables

The figures presented in the appendix provide a comprehensive overview of key descriptive statistics for item features such as price, condition, size, and text length.

Figure 10 shows the distribution of item prices, with most items priced between 0 and 5000 NOK, highlighting a concentration of lower-priced items. This distribution is consistent with the tendency of online marketplaces to cater to price-sensitive consumers. Additionally, the distribution of item conditions, shown in Figure 11, reveals that most items fall under the categories “New” or “Lightly Used,” with fewer items categorized as “Well Used” or lacking a specified condition. This skew suggests that buyers may prefer items in better condition, which aligns with expectations in second-hand markets.

The distribution of product sizes, shown in Figure 12, highlights that medium-sized items (M) dominate the listings, followed by small (S) and large (L) sizes. The distribution of time to sell, presented in Figure 13, demonstrates that the majority of items sell within a few hundred days, though there are outliers that take much longer to sell, with the distribution capped at two years.

Text-related features, including title and caption lengths, are detailed in Figures 14 and 15. Titles are generally short, with the majority falling into the “s” (short) category of fewer than 10 characters, while captions exhibit greater variability, with many items either lacking a caption or using a caption of moderate length (between 75 and 150 characters). Finally, the price quintiles, calculated per category and per month, are depicted in Figure 16. This figure reveals that the distribution of items across quintiles is fairly uniform, suggesting a balanced segmentation of item prices within their respective categories over time, with a slight major presence of cheaper items.

2.4 Developing variables related to images

2.4.1 Profile Picture Analysis

In this study, a comprehensive analysis was conducted on all profile pictures to extract and quantify a wide range of visual characteristics. The variables identified include the category of the image, which differentiates between whether the image primarily features a face or a full person. The size_ratio variable measures the proportion of the image occupied by the identified object relative to the total image size, providing insights into the prominence of the subject within the frame.

The composite score, which is detailed further in the appendix, evaluates the aesthetic appeal or beauty of the profile picture using a CLIP model[3], a neural network that encodes images and their descriptions. Additionally, detailed facial and body keypoints were extracted, including the positions of the nose, eyes, ears, shoulders, elbows, wrists, hips, knees, and ankles. These keypoints allow for a fine-grained analysis of the posture and orientation of the person in the image.

Moreover, the variables age and gender were estimated using the MiVOLO (Kuprashevich and Tolstykh, 2023) model, a robust tool known for its accuracy in demographic classification. The number of faces (n_faces) and the number of persons (n_persons) in the image were also recorded, providing further context about the nature of the profile pictures. This detailed analysis of profile pictures allows for a nuanced understanding of how visual attributes might influence outcomes in second-hand marketplaces.

2.4.2 Labeling the pictures as Person Self, Homemade Cloth, Professional Model, Professional Cloth

The image analysis was conducted using a model trained with YOLOv8 by Ultralytics. Initially, the YOLOv8 large classification weights, pre-trained on a broad dataset, were fine-tuned to develop a custom model. The model achieved an 89% success rate in out-of-sample validation.

Given the impracticality of manually analyzing all images, a semi-supervised learning approach was employed. First, a training set was created for the "tops" category, starting with 500 training images, and 100 validation images. This process was iterated six times, ultimately expanding the dataset to 1,600 training images and 500 validation images. The lower bound for validation images

[3]CLIP (Contrastive Language-Image Pretraining), is a neural network model developed by OpenAI that can understand and associate images with textual descriptions. It works by training on a large dataset of images and their corresponding text, learning to align visual and textual information. CLIP can be used for various tasks, such as image classification, zero-shot learning, and content-based image retrieval, by evaluating how well an image matches a given text prompt. Its versatility and ability to generalize across different tasks make it a powerful tool in the field of multimodal AI.

resulted from the underrepresentation of the “Professional Clothing” category.

In this approach, the initially trained model was used to label additional images. These automatically labeled images were then manually reviewed, and the corrected labels were used to retrain and improve the model further.

The refined model was subsequently applied to categorize images for “Jumpsuits” “Skirts” and “Pants” These categories were selected to represent the “top” “full-body” and “bottom” segments of clothing, respectively.

The last step involved training the classifier using the pre-trained YOLOv8 large model, fine-tuned over 100 epochs. We utilized 62,5% of the 3.200 labeled images for training and 37,5% for validation. The YOLOv8 model, already equipped with robust transfer learning Hartmann et al. (2021), Zhang et al. (2021), and Zhang and Luo (2022), data augmentation (Krizhevsky et al., 2012), and regularizationtechniques (Srivastava et al., 2014), effectively mitigates overfitting without requiring additional manual intervention. This streamlined approach allowed us to achieve high performance with minimal adjustments to the standard training process. Once classified, a dummy variable was generated according to the type of subject in the picture.

To create the control variables, I utilized a combination of open-source models. The presence of a person in the image was detected using the MiVOLO model (Kuprashevich and Tolstykh, 2023), which also provided estimates for the person’s age. For assessing beauty, I employed the CLIP model, applying it to image crops generated by MiVOLO. Image quality measures, such as resolution and the detection of duplicate images, were calculated using the CleanVision library[4]. This tool also identified whether images were too dark or too light, contributing to the overall quality assessment.

For the clothing-specific variables, the CLIP model was again used to determine whether the garment appeared ironed and to evaluate the environment in which the clothing was presented—whether it was a fancy or messy setting. The vibrancy of the garment colors was also assessed using CLIP. Additionally, dummy variables were created to indicate whether a face was present in the image, whether the subject appeared to be with a boyfriend or girlfriend, and to measure the relative size of the face or body within the image.

In our analysis, CLIP was employed to quantitatively assess the neatness of an image’s background. This approach leverages the model’s ability to understand and compare complex visual and textual concepts. Specifically, we evaluated each image against a set of positive descriptors (e.g., “a neat and clean background”) and negative descriptors (e.g., “a messy background”). By calculating the similarity between the image and these descriptors, we derived a neatness score, which serves as a robust metric for background quality. This automated method provides a consistent and objective measure that can be crucial in evaluating the presentation quality of products in online marketplaces. Such a metric is particularly valuable in marketing and economics research, where visual presentation can significantly influence consumer behavior and purchasing decisions.

[4]`https://github.com/cleanlab/cleanvision`

Humans are inherently visual creatures, making the visual presentation of products crucial in online marketplaces. Previous research has shown that visual appeal significantly influences consumer behavior and decision-making in online environments (Belém et al., 2019). The design of these platforms often reinforces this tendency by incentivizing users to post images that include themselves, mirroring the practices of influencers. Studies have demonstrated that consumers are more likely to trust and engage with sellers who use personal photos, as this aligns with social media trends where personal branding and visual storytelling are key to engagement (Athey et al., 2022). By encouraging users to emulate influencers, the platform taps into established consumer behavior patterns, where the visual appeal of a product, coupled with the perceived authenticity of the seller, can significantly drive purchasing decisions (Ma et al., 2019). This interplay between human visual preferences and platform design choices underscores the importance of image quality and presentation in shaping consumer behavior.

3 Empirical Framework

This analysis focuses on understanding the dynamics of marketplace outcomes by examining the influence of various factors, with particular attention to the *image category* in the first product image. The person category captures the presentation style of the item, which can take four distinct values: *informally presented cloth*, *well presented cloth*, *professional model*, and *real person*. We hypothesize that the presentation style significantly influences the likelihood of a sale and the time it takes for a product to sell.

Our analysis proceeds by investigating three primary aspects of marketplace dynamics. First, we examine the factors influencing the initial listing price of products. This analysis employs a linear regression model to explore how product characteristics, seller reputation, and, critically, the person category of the first image, impact the price-setting behavior of sellers.

Second, we assess the likelihood of a product being sold, using a linear probability model. The binary outcome (whether the product sells) is modeled as a function of pricing strategies, seller reputation, and the presentation of the product. Here, particular attention is paid to the *image category* of the first picture, as we expect it to play a crucial role in capturing consumer attention and driving sales.

Lastly, we explore the factors influencing the speed of sale for products that are successfully sold. In this case, we employ a *linear regression*, analyzing how *image category* of the first image affect the time-to-sell controlling for pricing, seller reputation, and "experience" on the platform.

The following sections will detail the econometric models employed for each dimension of the analysis and provide a comprehensive interpretation of the results.

3.1 The Models

3.1.1 How does image category affects posting behavior?

$$
\begin{aligned}
p_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture}_j + \\
&+ \beta_1 \cdot \text{Reputation} + \beta_2 \cdot \text{Experience}_t \\
&+ \beta_3 \cdot \chi_{i,j} + \epsilon_{i,j,t}
\end{aligned} \tag{1}
$$

- $p_{i,j}$: Predicted price for product i and individual j.
- α_i: The intercept term specific to product i, capturing product-specific effects.
- ProductPicture_i: Set of variables representing the visual aspects of the product image, including whether a product picture is present, if the seller is present in the image, and the aesthetic quality or beauty of the image.
- Reputation_j: Set of variables reflecting the individual's reputation, measured by the number of reviews and the overall score or rating they have received.
- $\text{Experience}_{j,t}$: This variable accounts for the individual's experience, indicated by the number of products they have posted and sold at given time t (including those not reviewed).
- $\chi_{i,j}$: A set of controls representing other factors such as the bio of the seller and the description of the product, the category of the product, and brand.
- $\epsilon_{i,j,t}$: The error term capturing unexplained variability in the dependent variable for product i and individual j at time t.

3.1.2 How does image category affects purchasing choices?

In addition to predicting price, we can use a logit model to examine the likelihood of a product being sold or remaining unsold. This model will include the same predictors as the linear regression, with the addition of price as a control variable:

$$
\begin{aligned}
SaleOutcome_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \\
&+ \beta_1 \cdot \text{Reputation}_j + \beta_2 \cdot \text{Experience}_t \\
&+ \beta_3 \cdot \chi_{i,j} + \beta_4 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t}
\end{aligned} \tag{2}
$$

Where:

- $\text{SaleOutcome}_{i,j}$ is a binary variable indicating whether the product i was sold (1) or remained unsold (0).
- $\text{Price}_{i,j}$ is the control variable representing the price of the product i.

3.1.3 How does image category affects purchasing choices?

For products that are sold, a linear regression model can be used to predict the time it takes to sell the product, considering the same factors:

$$\begin{aligned}\text{TimeToSell}_{i,j} = {} & \alpha_i + \beta_0 \cdot \text{ProductPicture}_j + \\ & + \beta_1 \cdot \text{Reputation}_j + \beta_2 \cdot \text{Experience}_t \\ & + \beta_3 \cdot \chi_{i,j} + \beta_4 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t}\end{aligned} \tag{3}$$

Where:

- $\text{TimeToSell}_{i,j}$ represents the time it took to sell product i by individual j, for those products that were sold.

4 Results

This section presents the results. The key findings are summarized in the tables and figures below.

Table 3 displays the effect of different types of the item picture on the posting price, relative to the reference category "Cloth Self" (where only the piece of clothing is shown without a model, a real person or using a stock image, or carefully laid).

The results highlight the significant impact of the *Real Person* presentation strategy on product prices. In column (8), which includes both *category-date interaction fixed effects*, *user fixed effects* and *brand fixed effects*, the presence of a real person in the product presentation is associated with a 15.6% increase in the posting price. This result remains highly significant even after controlling for a comprehensive set of covariates, including text, review, and experience variables. This suggests that buyers may perceive listings featuring real people as more trustworthy or appealing, thereby driving higher prices. Interestingly, while the effect size of the real person variable diminishes slightly compared to earlier models (e.g., from 30.3% in column (1)), the significance remains consistent, indicating a robust relationship between real person presentations and posting prices.

Table 3: Posting Prices Regression

Dependent Variable:	log(price)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Well Presented Cloth	0.575***	0.556***	0.480***	0.416***	0.428***	0.297***	0.296***	0.219***
	(0.058)	(0.060)	(0.052)	(0.049)	(0.049)	(0.037)	(0.036)	(0.023)
Professional Model	0.589***	0.563***	0.485***	0.425***	0.416***	0.275***	0.274***	0.240***
	(0.054)	(0.057)	(0.052)	(0.042)	(0.042)	(0.030)	(0.030)	(0.017)
Real Person	0.303***	0.298***	0.243***	0.174***	0.166***	0.157***	0.157***	0.152***
	(0.044)	(0.045)	(0.043)	(0.038)	(0.039)	(0.032)	(0.032)	(0.021)
Condition	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓
Person in Profile Picture					✓	✓	✓	✓
Fixed-effects								
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User FE						Yes	Yes	Yes
Category FE-Date FE							Yes	Yes
Brand FE								Yes
Fit statistics								
Observations	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493
R^2	0.20146	0.20681	0.24634	0.29097	0.29828	0.63252	0.63847	0.73569
Within R^2	0.07703	0.08321	0.12890	0.18049	0.18894	0.16494	0.16461	0.13689

Clustered (Category FE) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.05, *: 0.1*

Table 4 presents the results from a series of regressions examining the relationship between product presentation, particularly the category of the person in the first image, and the likelihood of a sale. The reference category in these regressions is "Cloth Self," where only the piece of clothing is shown without a model or a real person. The models progressively add covariates and fixed effects to account for potential confounders.

The results underscore the importance of presentation strategy in driving sales outcomes. Across all models, *Well Presented Cloth* and *Professional Model* significantly increase the probability of a sale relative to the baseline category, with the effect remaining highly robust across specifications. For instance, in column (9), which includes *category-date interaction fixed effects*, *user fixed effects*, and *brand fixed effects*, the presence of a well-presented cloth is associated with a 4.4 percentage point increase in the probability of sale, while using a professional model increases the probability of sale by 5.3 percentage points.

Interestingly, the impact of a *Real Person* in the first image is less pronounced. While it remains statistically insignificant in early models, in the final model (column (9)), the use of a real person is associated with a 1.4 percentage point increase in the probability of sale, and this effect becomes significant at 1% level. This suggests that while more professional presentation styles (e.g., well-presented cloth and professional models) exert a stronger influence on sales, real person imagery still increases sales with respect to informally presenting the cloth, but to a lower extent.

The models also control for important covariates such as product condition, price quintile, review variables, and seller experience, all of which exhibit expected signs. The inclusion of fixed effects for categories, dates, users, and brands ensures that these results are not driven by unobserved heterogeneity at the category or seller level.

Overall, these results highlight the nuanced role of visual presentation in marketplace dynamics. The choice of using professional models or well-presented cloth has a consistently strong impact on sales, while real person imagery, though weaker in its effect, shows significance in the final model.

Table 4: Sold Unsold Regression

Dependent Variable:					sold				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Well Presented Cloth	0.116***	0.117***	0.099***	0.086***	0.066***	0.067***	0.057***	0.058***	0.044***
	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)	(0.007)	(0.002)	(0.002)
Professional Model	0.120***	0.121***	0.103***	0.088***	0.067**	0.067**	0.055**	0.056***	0.053***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.016)	(0.001)	(0.001)
Real Person	0.023	0.024	0.011	0.011	0.003	0.004	0.012	0.013***	0.014***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.013)	(0.001)	(0.001)
Condition	✓	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓	✓
Price Quintile					✓	✓	✓	✓	✓
Person in Profile Picture						✓	✓	✓	✓
Fixed-effects									
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User FE							Yes	Yes	Yes
Category FE-Date FE								Yes	Yes
Brand FE									Yes
Fit statistics									
Observations	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493	1,696,493
R^2	0.04061	0.04068	0.04825	0.10253	0.11023	0.11067	0.36514	0.37475	0.39433
Within R^2	0.00973	0.00980	0.01762	0.07364	0.08159	0.08205	0.04234	0.04242	0.02984

*Signif. Codes: ***: 0.001, **: 0.05, *: 0.1*

Table 5 presents the regression results examining the relationship between product presentation—specifically the person category in the first image—and the logarithm of time to sell. The reference category for these regressions is "Cloth Self", where only the clothing item is presented without a person or model. The results indicate that the presentation style has a significant impact on how quickly a product sells.

In the initial specifications (columns 1 through 6), the coefficients for *Well Presented Cloth*, *Professional Model*, and *Real Person* all exhibit negative and significant effects on *log(TimeToSell)*, indicating that these presentation styles are associated with faster sales relative to the baseline category. For example, in column (4), which includes text, review, and experience variables, a well-presented cloth is associated with a 16% reduction in the time to sell, while a professional model reduces the time to sell by approximately 13.6%. Similarly, using a real person in the first image is associated with a 14.3% reduction in the time to sell, reflecting a substantial effect.

However, as additional covariates and fixed effects are introduced in the later specifications (columns 7 through 9), the relationship between presentation style and time to sell weakens. In the most comprehensive model (column 9), which includes *category-date interaction fixed effects*, *user fixed effects*, and *brand fixed effects*, the coefficients for *Well Presented Cloth* and *Professional Model* become positive and significant, indicating a shift in the relationship. Specifically, a well-presented cloth is now associated with a 7.7% increase in the time to sell, while the professional model category shows a similar effect (7.7%). Interestingly, the *Real Person* category becomes insignificant, suggesting that its initial effect may be driven by other factors captured by the fixed effects.

These results suggest that while presentation style has a clear impact on time to sell in simpler models, the inclusion of more comprehensive controls and fixed effects reveals a more nuanced picture. The positive relationship between presentation style and time to sell in the final specification may indicate that certain presentation strategies are more common for higher-priced items or items in categories that naturally take longer to sell.

4.1 Diving into Categories

There is noticeable heterogeneity in how image categories affect product outcomes across various types of clothing items. Specifically, the impact on prices, sales, and time to sell varies depending on both the product category (e.g., dresses, jackets, or fitness wear) and the type of image used in the listing. For instance, using professional models, real people, or well-presented clothing displays influences these outcomes in distinct ways, and not all categories respond similarly to these image types. Some categories may experience a greater uplift in sales or pricing when using professional models, whereas others may benefit more from simpler, well-presented photos.

The data supports the notion that presentation strategies play a crucial role in shaping marketplace dynamics, with the type of image selected influencing the consumer's decision-making process. Specifically, as can be seen in Figures 17,

Table 5: Time to Sell Regression

Dependent Variable:	log(TimeToSell)								
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Well Presented Cloth	-0.152***	-0.157***	-0.149***	-0.160***	-0.066*	-0.053	0.033	0.036***	0.077***
	(0.035)	(0.034)	(0.035)	(0.038)	(0.033)	(0.033)	(0.025)	(0.009)	(0.009)
Professional Model	-0.145**	-0.152***	-0.144**	-0.136**	-0.032	-0.028	0.052*	0.055***	0.077***
	(0.040)	(0.039)	(0.040)	(0.052)	(0.041)	(0.041)	(0.030)	(0.007)	(0.007)
Real Person	-0.103**	-0.105**	-0.101**	-0.143**	-0.102**	-0.097**	-0.001	-0.0002	0.011
	(0.032)	(0.031)	(0.032)	(0.039)	(0.031)	(0.030)	(0.026)	(0.007)	(0.007)
Condition	✓	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓	✓
Price Quintile					✓	✓	✓	✓	✓
Person in Profile Picture						✓	✓	✓	✓
Fixed-effects									
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
User FE							Yes	Yes	Yes
Category FE-Date FE								Yes	Yes
Brand FE									Yes
Fit statistics									
Observations	910,018	910,018	910,018	910,018	910,018	910,018	910,018	910,018	910,018
R^2	0.39403	0.39409	0.39428	0.43487	0.44101	0.44137	0.59890	0.60970	0.62192
Within R^2	0.00106	0.00115	0.00148	0.06839	0.07850	0.07910	0.13451	0.13723	0.13694

*Signif. Codes: ***: 0.001, **: 0.05, *: 0.1*

18, and 19, certain categories—such as dresses and jackets—exhibit stronger reactions to the use of professional models in terms of price increases, while others—like pants and shorts—show an increase in sales when a professional model is present. This suggests that sellers must carefully consider both the category of their product and the most effective image type to optimize their listings for better market performance.

4.2 Does Beauty Matter?

Appearances were classified using CLIP, a neural network model developed by OpenAI that can associate images with descriptive text. Each profile picture was assigned an appearance score between 0 and 100, which were then divided into quintiles to create five distinct groups for analysis. The distribution of beauty scores appears to follow a normal distribution, as shown in Figures 20 and 21, both for unique users and generally across all users who post products on the platform.

While appearance interacts with the image category to produce varied effects on product outcomes, our analysis indicates that beauty has a noticeable effect on sales but not much effect on pricing as shown in figures 22 and 23. Although higher appearance scores can enhance engagement and increase the likelihood of a sale, listings featuring professional models or well-presented products consistently outperform others in terms of sales, as demonstrated in previous sections. Therefore, professional presentation strategies appear to mitigate the need to rely on personal appearance as a driving factor for success in product listings.

5 Conclusion

This study investigates the impact of image categories on posting behavior, pricing strategies, sales performance, and time-to-sell within the second-hand fashion marketplace, utilizing comprehensive data from Tise.com. Our analysis reveals that the presentation style of product images plays a crucial role in shaping various market outcomes. Specifically, listings featuring a *Real Person* in the product image are associated with a substantial 15.6% increase in posting price, suggesting that consumers perceive these listings as more trustworthy and appealing, thereby justifying higher price points.

In terms of sales performance, both the *Well Presented Cloth* and *Professional Model* image categories enhance the likelihood of a sale by 4.4 and 5.3 percentage points, respectively. This indicates that professional and aesthetically pleasing presentations are effective in increasing consumer trust and product desirability, leading to higher conversion rates. Although the *Real Person* category also positively influences sales probability, its effect is relatively modest compared to more professional presentation styles, with a 1.4 percentage point increase.

Moreover, our analysis of appearance scores reveals that while beauty has a noticeable effect on sales performance, it does not significantly influence pricing strategies. Listings associated with higher appearance scores show an increased likelihood of sale, suggesting that personal attractiveness can enhance engagement. However, professional presentation styles consistently outperform reliance on personal appearance alone, indicating that professional images are more effective in driving sales.

Regarding the time-to-sell, our findings present a nuanced picture. While initial models suggest that enhanced presentation styles accelerate sales, the most comprehensive model reveals that the *Well Presented Cloth* and *Professional Model* categories are associated with an increase in the time required to sell a product.

Overall, the results underscore the critical role of visual presentation in online marketplaces. Effective image categorization can influence not only pricing and sales outcomes but also the dynamics of how quickly products are sold. These insights are valuable for sellers aiming to optimize their listing strategies to enhance market performance. Future research could explore the underlying mechanisms driving the relationship between image presentation, personal appearance, and time-to-sell, as well as extend the analysis to other product categories and marketplaces to generalize the findings. Additionally, investigating the interaction between image quality, personal appearance, and other listing attributes—such as descriptive text and pricing strategies—could provide a more holistic understanding of consumer decision-making processes in second-hand markets.

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Appendix

5.1 Products

Informal setting without person

Pro-like setting without person

Informal setting with person

Professional setting with person

Figure 1: Examples of product display

5.2 Data Description

A Descriptive Statistics - Plots

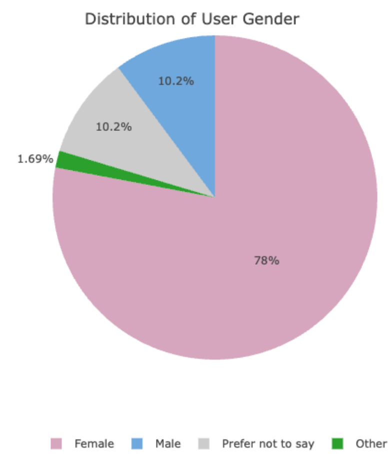

Figure 2: Distribution of User Gender

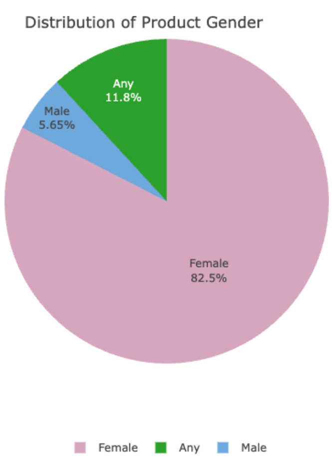

Figure 3: Distribution of Product Gender

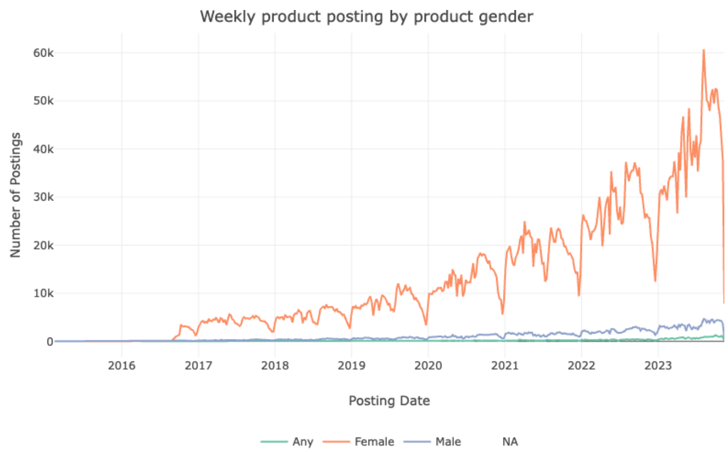

Figure 4: Weekly Product Postings by Product Gender

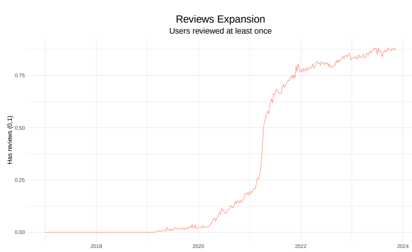

Figure 5: Expansion of User Reviews Over Time

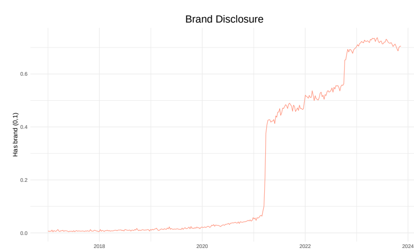

Figure 6: Brand Disclosure Over Time

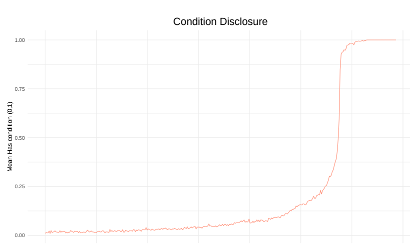

Figure 7: Condition Disclosure Over Time

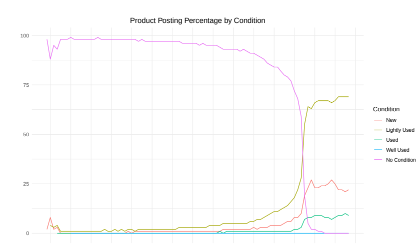

Figure 8: Product Posting Percentage by Condition

Figure 9: Changes in Platform Features Over Time

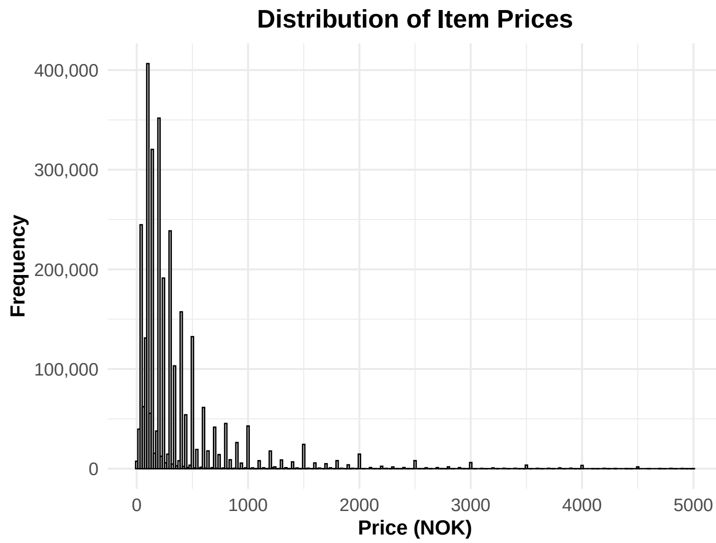

Figure 10: Distribution of Item Prices. The histogram shows the distribution of item prices rounded to the nearest NOK 10.

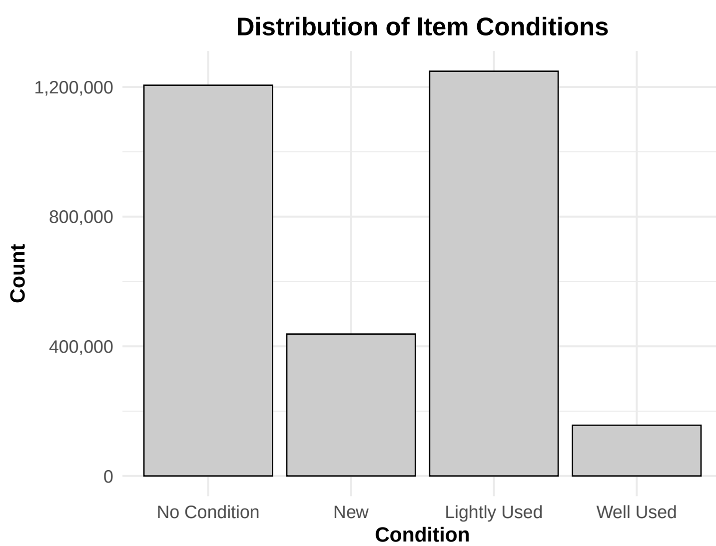

Figure 11: Distribution of Item Conditions. Conditions include categories such as “No Condition,” “New,” “Lightly Used,” and “Well Used.”

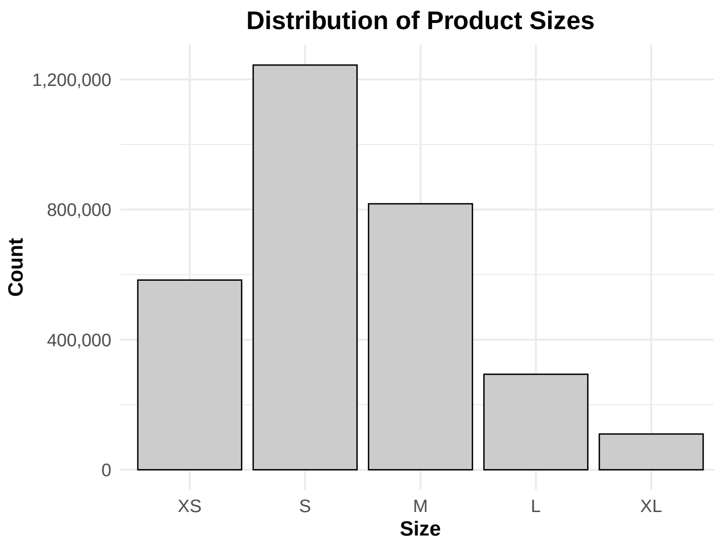

Figure 12: Distribution of Product Sizes. The sizes are categorized as XS, S, M, L, and XL.

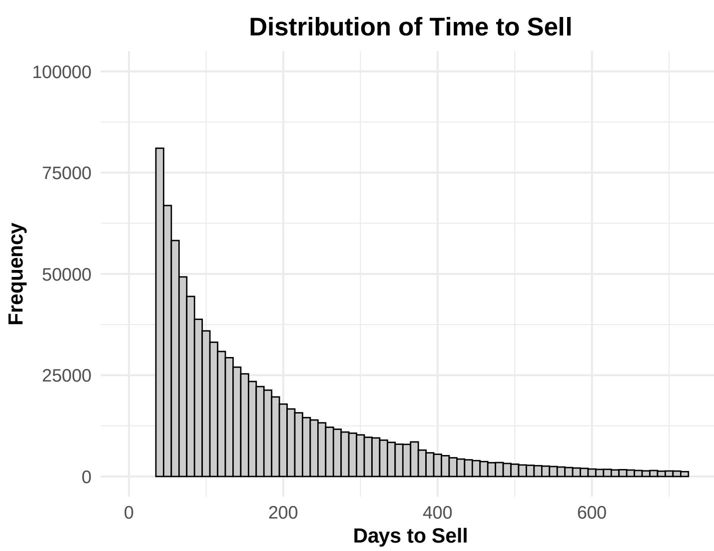

Figure 13: Distribution of Time to Sell. This histogram shows the number of days it took to sell items, for items that were sold. The distribution is capped at 730 days (2 years).

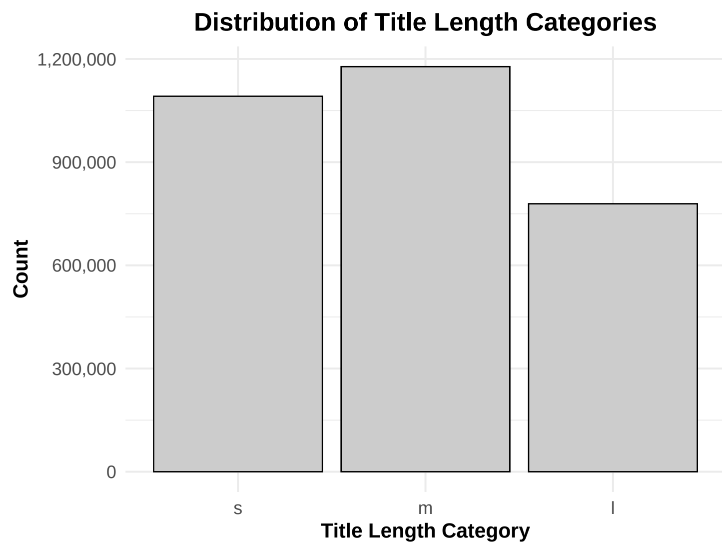

Figure 14: Distribution of Title Length Categories. Title lengths are divided into bins: "s" (0-10 characters), "m" (11-15 characters), and "l" (16+ characters).

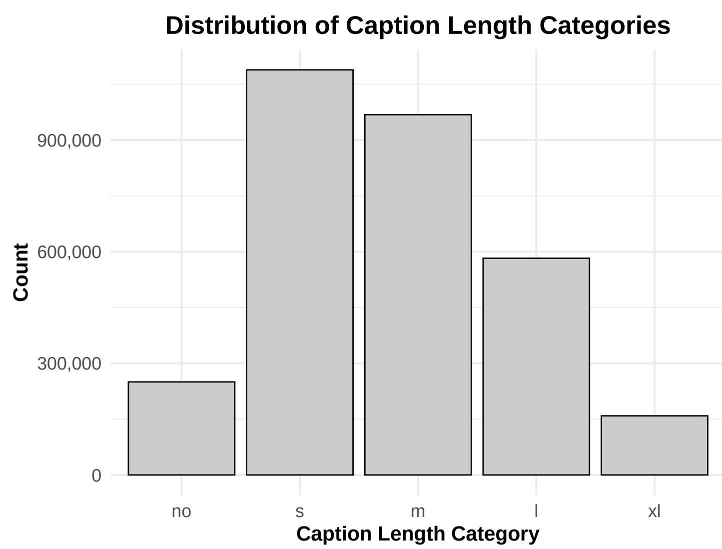

Figure 15: Distribution of Caption Length Categories. Captions are categorized into: "no" (0 characters), "s" (1-75 characters), "m" (76-150 characters), "l" (151-300 characters), and "xl" (301+ characters).

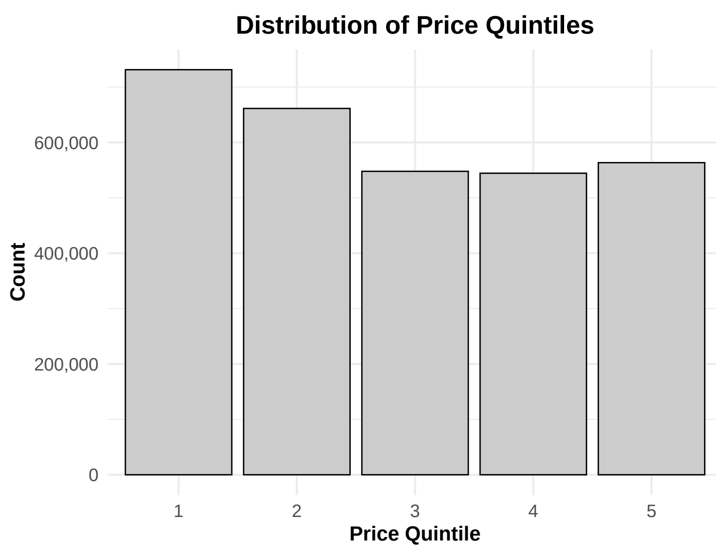

Figure 16: Distribution of Price Quintiles. Quintiles are calculated per category, per month, and show the frequency distribution of items across quintiles 1 to 5.

B Categories

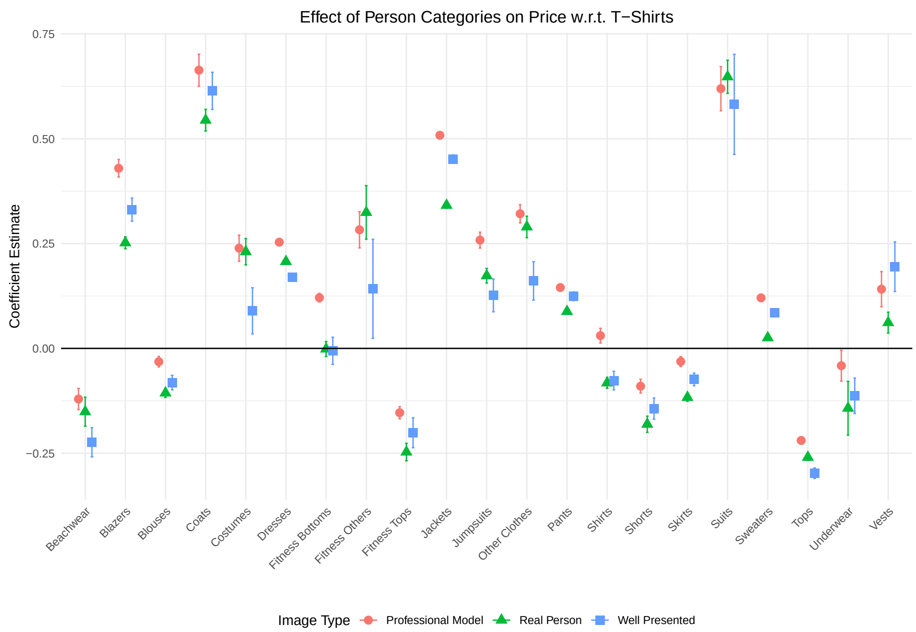

Figure 17: Effect of Person Categories on Prices: The coefficients show the impact of different person categories (e.g., professional model, real person, well-presented) on the pricing of second-hand clothing items.

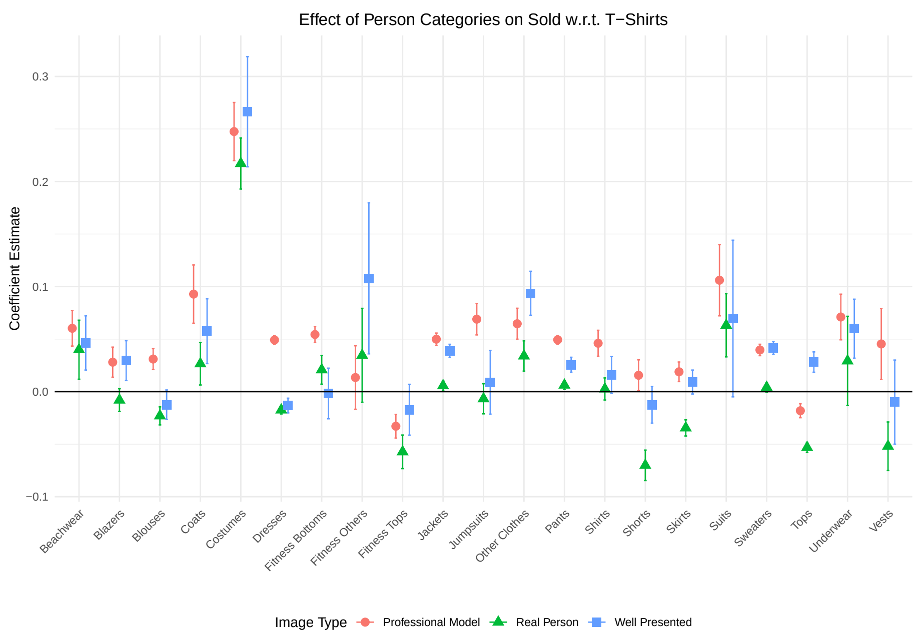

Figure 18: Effect of Person Categories on Sales Probability: This plot demonstrates how different person categories influence the likelihood of a product being sold, compared to the reference category.

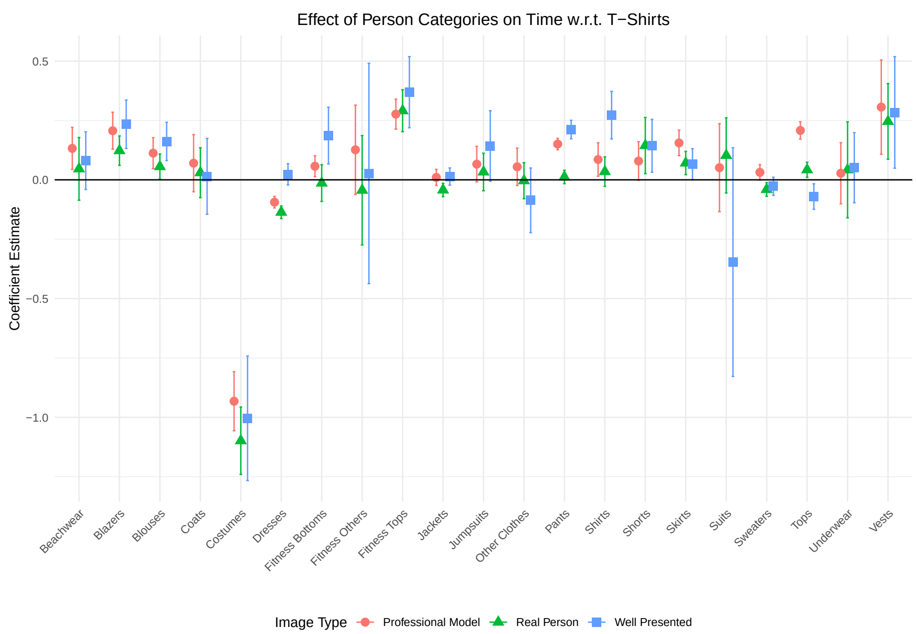

Figure 19: Effect of Person Categories on Time-to-Sell: The plot shows the relationship between person categories and the time it takes to sell a product. Negative coefficients indicate faster sales.

C Beauty

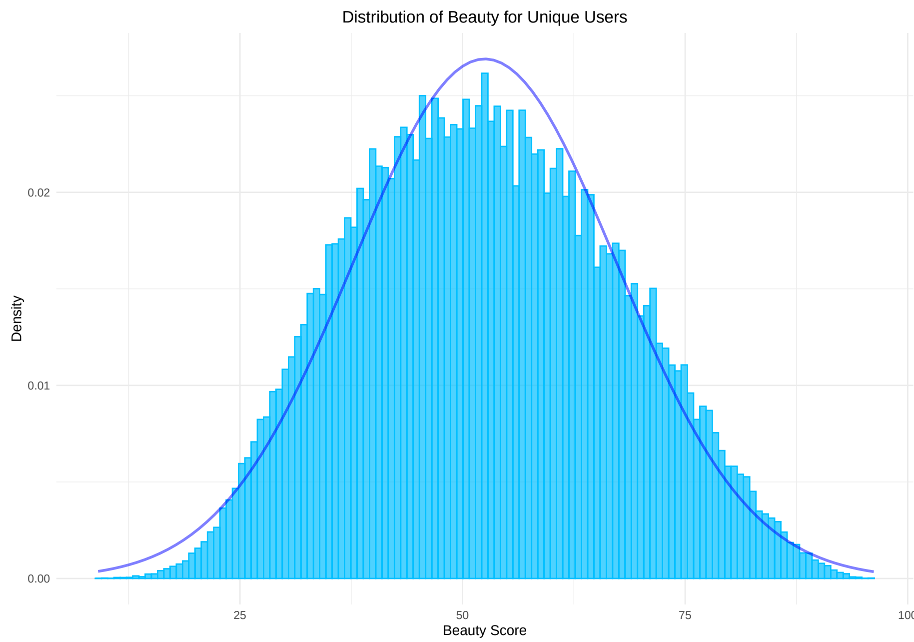

Figure 20: Distribution of Beauty Scores for Unique Users: The distribution of appearance scores assigned to unique users posting products, with beauty classified into quintiles.

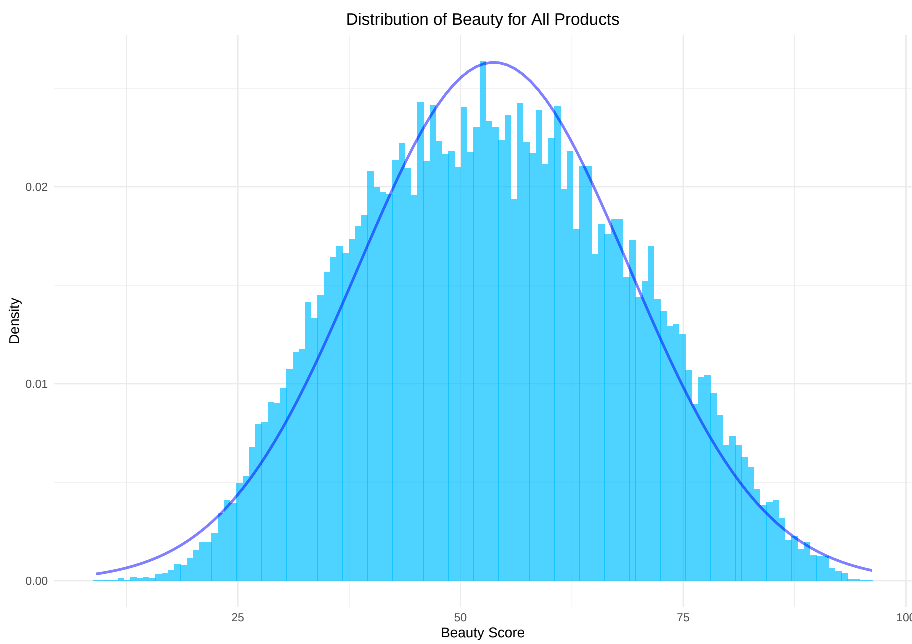

Figure 21: Distribution of Beauty Scores for All Users: The appearance scores of all users who post products on the platform, showing how beauty is distributed across the marketplace.

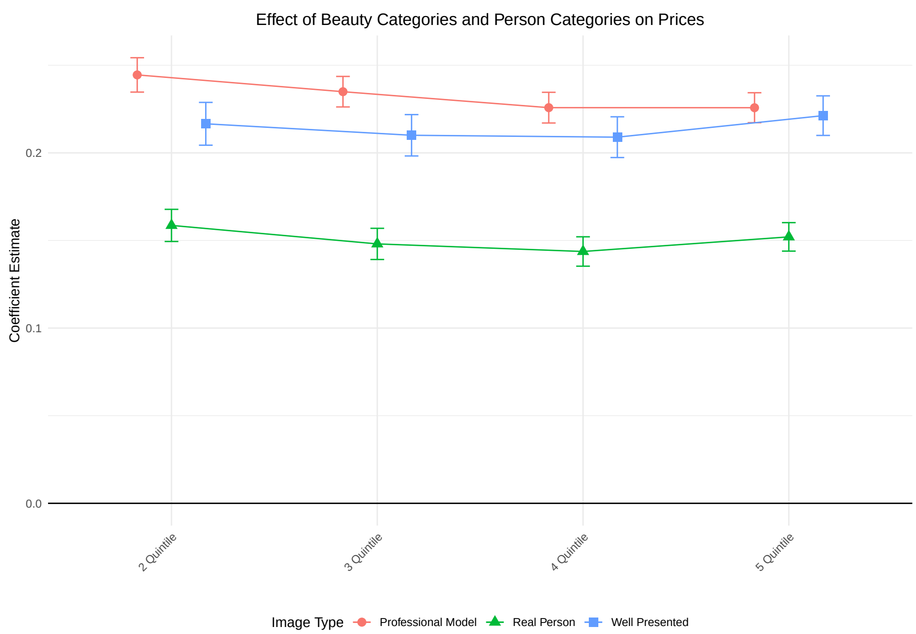

Figure 22: Effect of Person Categories on Prices (General): This plot reflects the overall impact of person categories, including appearance scores, on the pricing behavior across different product listings.

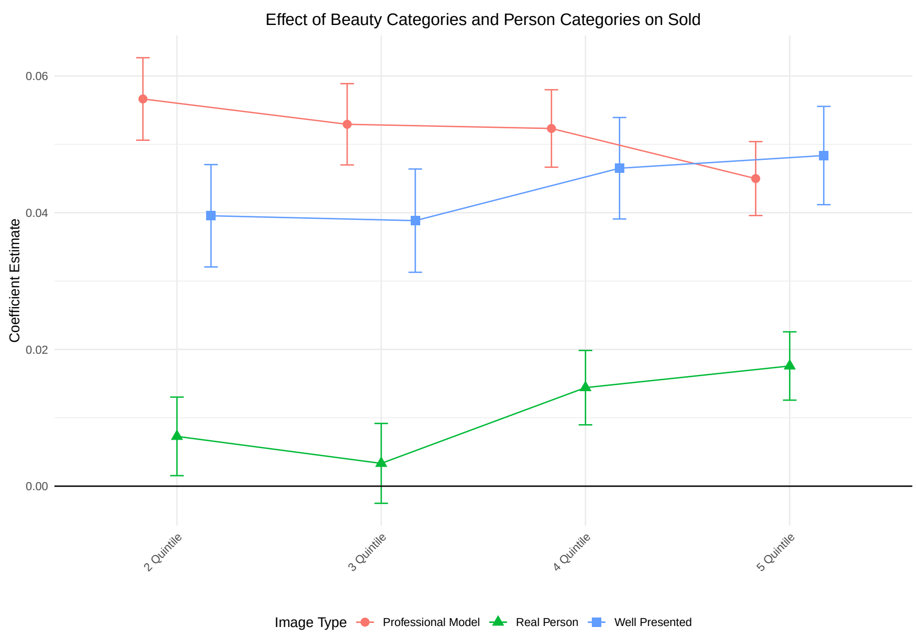

Figure 23: Effect of Person Categories on Sales (General): The graph demonstrates how person categories, including user appearance scores, influence the likelihood of a product being sold.