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

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valuable insights into leveraging visual appeal to enhance their business performance in a crowded market.

Motivation

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, 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,

[1]Source: Startup on tise.com

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 presentable." 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].

First, perceptions of product fit may be formed holistically, based on multiple visual cues in the listing photos, many of which could extend beyond basic product information. For example, visual cues such as the cleanliness and presentation of the item can influence perceptions of its quality and desirability, which may well influence perceptions of fit for specific needs (e.g., formal occasions vs. casual wear). Second, perceptions of product fit could be category-specific, i.e., the same product might be perceived differently depending on the category under consideration. For instance, while a "vintage-looking" item (condition and brand held constant) may be perceived as a high fit for a retro fashion enthusiast, it may be perceived as a low fit for someone seeking modern, contemporary styles.

In addition to this, the product "fit" can be perceived also in relation of the setting its is presented. For example, the product can be displayed in different ways, such as: using store or stock photos, or presenting it in an informal way, for example in room or as well in a scenic way, with a landscape. For clothing, the product can be also show worn or lying on a surface. In figure 1 I show some common product display on the platform.

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 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)

[2] Source: tise.com Guidelines

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. Options include taking a picture in a real-life setting, ironing the clothing, wearing it, and capturing a well-lit photograph. These decisions significantly impact 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 setting of a product photo influence consumer purchasing decisions in second-hand marketplaces?
- What impact does the presence of a person in product photos have on the perceived value and attractiveness of the item?
- To what extent does the perceived professionalism of a product photo affect its likelihood of being sold?
- How does the beauty of the product, as captured in photos, affect consumer perceptions and purchasing behavior?
- How do privacy concerns influence seller decisions regarding the inclusion of personal elements in product photos?
- What is the interplay between review systems and the quality of product photos in influencing consumer trust and purchase decisions?

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

My study use data from tise.com, that is a prominent second-hand fashion platform primarily serving the Nordic region, encompassing countries such as Norway, Sweden, Denmark, and Finland. The platform is designed to facilitate the buying and selling of pre-owned fashion items, integrating various features to enhance user experience and safety. Key functionalities include an integrated payment solution that ensures secure transactions, a robust search system for specific categories and brands, and options for users to earn extra income through reselling.
The app also emphasizes sustainable shopping by encouraging the reuse and recycling of fashion items, thereby contributing to environmental conservation efforts. Users can upload photos of their items, trying to sell them through the platform. Additionally, Tise offers features for browsing the latest fashion trends, which helps users stay updated with current styles while shopping second-hand.
The community aspect of Tise is significant, with millions of active users who interact within the platform, thereby creating a dynamic marketplace environment. This user base not only drives the economic activity on the platform but also fosters a sense of community among second-hand fashion enthusiasts. The platform's design choices, including reputational systems and product presentation, play a crucial role in influencing purchasing decisions and building trust among users.
Specifically, we limit our analysis to adult clothing apparel, excluding categories such as child & baby, interior & furniture, outdoor, art & design, devices & audio, and leisure & hobbies. These excluded categories are retained solely for building metrics related to reputation and user experience on the marketplace.
The primary reasons for choosing Tise over Vinted, the leading second-hand marketplace in Europe, are as follows:

1. Single Market Structure: Unlike Vinted, where users can trade across multiple markets, Tise operates as a single market within each Nordic country. This separation ensures that users within each country interact solely with each other, providing a more localized and cohesive trading experience.

2. Global overview: Tise maintains a comprehensive history of user purchases, allowing for detailed tracking of wardrobes and user experiences. This feature provides valuable data for analyzing consumer behavior and market trends within the platform.

3. Flexibility in Photo Posting: Tise does not prohibit the use of "stock" or professional photos in listings, unlike Vinted. This policy provides a complete overview of posting behavior, offering insights into how different presentation strategies affect 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.
For each product listing, we scrape all the data available

2.1 Data Collection

Data was collected from tise.com using their hidden API, resulting in approximately 9 Million data points over 4 countries and spanning from January 2016 through March 2024, when the data retrieval was performed. For a clearer analysis, I decided to subset the data to only the country of Norway. This approach helps to reduce confounding factors such as different legislation, customs, habits, currencies, and behaviors present across the various Nordic countries. Norway is the origin country of Tise and has the highest usage rate of the platform, providing a rich dataset for analysis. Additionally, Norway lacks significant competitors in the second-hand marketplace sector, making it an ideal environment to study the impact of Tise without external market influences.
Subsetting the data to only Norwegian users, the data shrinks to 4.597.382 observations. The data spans across 22 categories.
The observation we use is at product level. Through the API we collect data about the product such as: category, condition, country of origin, reference gender, price, creation date, size, update date, brand, sold status, caption, colors and likes count.
For each user, it was collected the entire wardrobe, with history of sold products, review count, text and average rating.

2.2 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.

2.3 Developing variables related to images

2.3.1 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

[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.

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.

2.3.2 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 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 regularization (Srivastava et al., 2014)techniques, 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.

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 Data Analysis

The data analysis will focus on three key aspects of the marketplace dynamics. First, posting prices will be analyzed to determine the factors influencing the initial listing price of products. This analysis will consider variables such as product condition, and seller reputation. Second, the likelihood of a sale will

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

be examined to identify the elements that most significantly impact whether a product sells. Finally, for products that are sold, the analysis will explore what drives the speed of sale, assessing factors like pricing, product category, reputation, and picture analysis.

To analyze the data, different regression models will be employed based on the nature of the outcome variables. Linear regression will be used to assess what factors influence the posting prices, allowing us to evaluate continuous price outcomes. For the binary outcome of whether a product sells, a logistic regression (logit) model will be utilized to identify the key determinants of sales success. Finally, for products that are sold, a linear regression model will be applied to investigate the factors that drive the time it takes to sell, providing insights into the speed of sales.

The following sections will explore the models used for this

3.1 How does people presence affect posting behavior?

$$\begin{aligned} p_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\ &+ \beta_2 \cdot \text{Reputation} + \beta_3 \cdot \text{Experience}_t \\ &+ \beta_4 \cdot \chi_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{1}$$

- $p_{i,j}$: 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.
- ProfilePicture_j: Set of variables capturing details about the individual's profile picture, including whether a profile picture exists, if the individual is present in the picture, and the perceived attractiveness of the individual in 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.

3.2 How does people presence affect 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:

$$
\begin{aligned}
SaleOutcome_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\
&+ \beta_2 \cdot \text{Reputation}_j + \beta_3 \cdot \text{Experience}_t \\
&+ \beta_4 \cdot \chi_{i,j} + \beta_5 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

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.

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:

$$
\begin{aligned}
\text{TimeToSell}_{i,j} = \alpha_i &+ \beta_0 \cdot \text{ProductPicture} + \beta_1 \cdot \text{ProfilePicture}_j \\
&+ \beta_2 \cdot \text{Reputation}_j + \beta_3 \cdot \text{Experience}_t \\
&+ \beta_4 \cdot \chi_{i,j} + \beta_5 \cdot \text{Price}_{i,j} + \epsilon_{i,j,t} \qquad (3)
\end{aligned}
$$

Where:

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

4 Results

This section presents the results. The key findings are summarized in the table and figure below.

Table 1 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 (7), which includes both *category-date interaction fixed effects* and *user fixed effects*, the presence of a real person in the product presentation is associated with a 17.9% 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 30.9% in Model 1), the significance remains consistent, indicating a robust relationship between real person presentations and posting prices.

Column (8) provides additional insight, focusing solely on users with a profile picture. The analysis reinforces the importance of user characteristics. These results suggest that while presentation characteristics, such as the inclusion of a real person, significantly influence posting prices, the presence of a profile picture introduces additional user-specific factors that contribute to price-setting in online marketplaces.

Table 1: Posting Prices Regression

Dependent Variable:					log(price)				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Well Presented Cloth	0.570***	0.552***	0.470***	0.413***	0.413***	0.267***	0.268***	0.189***	0.424***
	(0.074)	(0.076)	(0.065)	(0.060)	(0.060)	(0.039)	(0.007)	(0.005)	(0.008)
Professional Model	0.600***	0.574***	0.491***	0.435***	0.434***	0.291***	0.292***	0.245***	0.446***
	(0.063)	(0.065)	(0.059)	(0.048)	(0.048)	(0.031)	(0.004)	(0.004)	(0.006)
Real Person	0.309***	0.305***	0.250***	0.190***	0.189***	0.178***	0.179***	0.169***	0.204***
	(0.049)	(0.049)	(0.045)	(0.038)	(0.038)	(0.030)	(0.004)	(0.004)	(0.005)
Condition	✓	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓	✓
Person in Profile Picture					✓	✓	✓	✓	✓
Profile Picture Info									✓
Fixed-effects									
Category FE	Yes	Yes	Yes	Yes	Yes	Yes			
Date FE	Yes	Yes	Yes	Yes	Yes	Yes			
User FE						Yes	Yes	Yes	
Category FE-Date FE							Yes	Yes	Yes
Brand FE								Yes	
Fit statistics									
Observations	469,483	469,483	469,483	469,483	469,483	469,483	469,483	469,483	369,519
R^2	0.22516	0.22992	0.27191	0.31226	0.31232	0.69739	0.71062	0.79508	0.35472
Within R^2	0.07675	0.08243	0.13246	0.18053	0.18061	0.14322	0.14290	0.11627	0.19564

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

Table 2 presents the results of a linear regression model, where the dependent variable is whether a product was sold (1) or not (0).

The variable Real Person, which indicates whether a real person is featured in the product presentation, shows an interesting progression across models. In Model 1, it is positive and significant, suggesting that featuring a real person increases the likelihood of a product being sold. However, as more controls are introduced, such as Text Variables, Review Variables, and Experience in Models 3 through 6, the effect of Real Person diminishes and becomes insignificant in Models 4 through 7.

Notably, in Model 8, when the interaction between Category and Date fixed effects is introduced, the Real Person variable becomes significant again. This suggests that the influence of using a real person in product presentation is context-dependent, varying across different product categories and time periods. The significance in Model 8 indicates that real-person presentations are particularly effective in certain contexts or time frames, possibly aligning with category-specific consumer behavior or seasonal trends.

Well Presented Cloth and Professional Model consistently have positive and highly significant effects on the likelihood of a product being sold across all models. However, the magnitude of these effects decreases as additional controls are introduced. For instance, the coefficient for Well Presented Cloth decreases from 0.133 in Model 1 to 0.067 in Model 8, suggesting that other factors, such as user experience or review information, explain part of the initial effect.

Fixed Effects: The introduction of User Fixed Effects in Model 7, along with the Category-Date interaction in Models 8 and 9, dramatically improves the model's fit, as evidenced by the large increase in R-squared from 0.100 in Model 6 to 0.431 in Model 7 and 0.451 in Model 8. This highlights the importance of accounting for both user-specific effects and time-category interactions in understanding sales outcomes.

In summary, while the Real Person presentation effect appears to weaken with the inclusion of additional controls, its re-emergence in Model 8 after introducing Category-Date interactions suggests that its influence is context-dependent. Overall, presentation characteristics, particularly Well Presented Cloth and Professional Model, play a significant role in driving sales, and their effects persist across various specifications. However, accounting for user-specific and temporal factors through fixed effects is crucial for fully understanding these dynamics in online marketplaces.
[5]

Table 3 presents a series of nine linear regression models analyzing the effect of various presentation characteristics on the logarithm of time to sell a product, conditional on the product having been sold. The dependent variable, log(TimeToSell), is regressed against presentation characteristics (such as Well Presented Cloth, Professional Model, and Real Person), with additional controls and fixed effects progressively added across models.

The variable Real Person, which indicates whether a real person is used in the product's presentation, shows consistent and significant results across models. In Model 1, the coefficient indicates that using a real person reduces the time to sell a product by approximately 13.4% on average. This effect remains significant throughout models, although it slightly decreases as more controls and fixed effects are introduced. Notably, in Model 5, after including experience and price quintile as controls, the coefficient for Real Person remains negative and significant, reinforcing the finding that using a real person in product presentations generally shortens the time to sell.

[5] Price quintile refers to the price being divided into quintiles based on the distribution of prices within the same product category for the given month. This allows for a relative comparison of prices within specific time periods and product categories.

Table 2: Sold Unsold Regression

Dependent Variable:	sold									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Well Presented Cloth	0.131***	0.132***	0.112***	0.103***	0.082***	0.082***	0.063***	0.065***	0.048***	0.064***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.013)	(0.013)	(0.008)	(0.004)	(0.004)	(0.004)
Professional Model	0.140***	0.142***	0.121***	0.112***	0.088***	0.087***	0.065***	0.067***	0.062***	0.067***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.015)	(0.003)	(0.003)	(0.003)
Real Person	0.039**	0.039**	0.026*	0.026	0.018	0.016	0.016	0.017***	0.018***	0.015***
	(0.014)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.013)	(0.003)	(0.003)	(0.003)
Condition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓	✓	✓
Price Quintile					✓	✓	✓	✓	✓	✓
Person in Profile Picture						✓	✓	✓	✓	✓
Profile Picture Info										✓
Fixed-effects										
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
User FE							Yes	Yes	Yes	Yes
Category FE-Date FE								Yes	Yes	Yes
Brand FE									Yes	
Fit statistics										
Observations	469,483	469,483	469,483	469,483	469,483	469,483	469,483	469,483	469,483	369,519
R^2	0.05570	0.05574	0.06485	0.09922	0.10726	0.10757	0.43330	0.45387	0.47802	0.45260
Within R^2	0.01311	0.01315	0.02267	0.05860	0.06699	0.06732	0.03113	0.03172	0.01891	0.03393

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

Table 3: Time to Sell Regression

Dependent Variable:	log(TimeToSell)									
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variables										
Well Presented Cloth	-0.141**	-0.149**	-0.144**	-0.205**	-0.091	-0.091	0.025	0.032	0.083**	-0.044**
	(0.060)	(0.059)	(0.061)	(0.067)	(0.058)	(0.058)	(0.045)	(0.026)	(0.026)	(0.022)
Professional Model	-0.118**	-0.128**	-0.123**	-0.172**	-0.048	-0.045	0.064	0.067***	0.092***	-0.006
	(0.053)	(0.051)	(0.054)	(0.067)	(0.053)	(0.052)	(0.046)	(0.019)	(0.020)	(0.016)
Real Person	-0.134***	-0.135***	-0.134***	-0.204***	-0.151***	-0.147***	-0.029	-0.035*	-0.020	-0.126***
	(0.032)	(0.032)	(0.034)	(0.037)	(0.028)	(0.029)	(0.049)	(0.021)	(0.021)	(0.016)
Condition	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Text Variables		✓	✓	✓	✓	✓	✓	✓	✓	✓
Review Variables			✓	✓	✓	✓	✓	✓	✓	✓
Experience				✓	✓	✓	✓	✓	✓	✓
Price Quintile					✓	✓	✓	✓	✓	✓
Person in Profile Picture						✓	✓	✓	✓	✓
Profile Picture Info										✓
Fixed-effects										
Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes			
User FE							Yes	Yes	Yes	
Category FE-Date FE								Yes	Yes	Yes
Brand FE									Yes	
Fit statistics										
Observations	212,517	212,517	212,517	212,517	212,517	212,517	212,517	212,517	212,517	170,125
R^2	0.42184	0.42193	0.42213	0.43386	0.44107	0.44116	0.68796	0.70695	0.72037	0.47485
Within R^2	0.00098	0.00113	0.00149	0.02175	0.03420	0.03436	0.11597	0.12530	0.12589	0.03787

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

However, in Model 7, where user fixed effects are introduced, the coefficient for Real Person becomes insignificant. This suggests that the variation in time to sell associated with using a real person is, in part, explained by unobserved characteristics of the users. In Model 8, when interaction terms between Category and Date fixed effects are introduced, the effect of Real Person regains significance, although the magnitude is smaller. This indicates that the influence of real-person presentations may vary by category and time, but it remains relevant across various product categories and seasons.

The variable Well Presented Cloth shows a consistent negative relationship with log(TimeToSell), indicating that a well-presented product tends to sell faster. While it remains significant across models, the magnitude fluctuates slightly as additional controls are added. In the final model (Model 8), the coefficient is still not significant.

The effect of Professional Model is significant in the early models but diminishes as more controls are introduced. By Model 6, the effect becomes insignificant, implying that the benefit of using a professional model may be partially explained by other factors, such as user experience or category-specific effects. In model 8, when category-fixed effects are introduced, the coefficient becomes significant and positive

The inclusion of user fixed effects in Model 7 drastically improves the model's fit, This suggests that user-specific characteristics are important factors in explaining variations in time to sell, indicating that certain users may have established reputations or practices that lead to faster sales. The Category-Date interaction fixed effects introduced in Model 8 further improve the model's fit, increasing the R-squared to 0.70695, indicating that temporal and category-specific factors significantly affect how quickly products sell.

Interpretation of the Last Column:

Model 9 focuses only on users with a profile picture, and in this model, the Real Person variable is again significant. This suggests that for users who display a profile picture, the use of a real person in the product presentation has a much stronger and more consistent effect in reducing the time to sell. This finding highlights the combined effect of user presentation (profile picture) and product presentation (real person) on driving faster sales.

In summary, the results indicate that the use of a Real Person in product presentations consistently shortens the time to sell, although its significance diminishes when accounting for user-specific factors. The introduction of user fixed effects and Category-Date interactions significantly improves model fit, suggesting that both user characteristics and temporal-category effects are important in understanding time-to-sell dynamics. The findings offer valuable insights for sellers on online marketplaces, highlighting the importance of well-presented listings, particularly when real people are featured, to accelerate sales.

Across all three tables, Real Person emerges as an influential factor, both in improving the likelihood of selling a product and reducing the time to sell. However, its effect is context-dependent, with significance fluctuating based on the inclusion of user, category, and temporal factors. The role of presentation elements like Well Presented Cloth and Professional Models is consistently positive across all models, indicating that well-curated presentations have a meaningful impact on both sales likelihood and time to sell.

4.1 Heckman selection model

Table 4: Heckman Selection Model: Time to Sell Regression

Dependent Variable:	log(TimeToSell)	
Model:	(1)	(2)
Variables		
Well Presented Cloth	-0.012 (0.017)	-0.075*** (0.020)
Professional Model	-0.002 (0.012)	-0.027* (0.014)
Real Person	-0.062*** (0.011)	-0.105*** (0.013)
Controls		
Text Variables	✓	✓
Review Variables	✓	✓
Experience	✓	✓
Price Quintile	✓	✓
Profile Picture Info	✓	✓
Fixed-effects		
Category FE	✓	✓
Week FE		✓
Day of the Week FE		✓
Fit statistics		
Observations	212,517	212,517
Log Likelihood	-499,016.400	-492,938.200
ρ	-0.992*** (0.0002)	-0.913*** (0.003)

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

Since using profile picture information reduces the sample size, as seen in Model 9 of the Time to Sell regression, the Heckman model helps retain all observations and correct for any selection bias introduced by the use of profile pictures.

Table 4 presents the results of two Heckman selection models examining the dependent variable log(TimeToSell), where the selection equation models whether a user has a profile picture. The Heckman model accounts for potential selection bias by correcting for the non-randomness of the sample, ensuring that the estimates for time to sell are unbiased despite the potential influence of user profile picture characteristics.

In both models, the variable Real Person shows a significant and negative relationship with log(TimeToSell), indicating that using a real person in product presentations reduces the time it takes to sell the product. In Model 1, the inclusion of a real person reduces the time to sell by approximately 6.2%. This effect becomes even stronger in Model 2, where more granular fixed effects (day of the week and week fixed effects) are added. This suggests that the real-person presentation continues to have a robust impact on speeding up sales, even when accounting for additional time-based fixed effects.

Interestingly, the impact of Well Presented Cloth and Professional Model varies across the two models: In Model 1, Well Presented Cloth is not significant, but in Model 2, its effect becomes significant, indicating a reduction in time to sell by 7.5%. Similarly, the Professional Model variable becomes significant at 10% in Model 2. This suggests that including professional models in product presentations may have a smaller but still meaningful effect in reducing the time to sell when time-specific effects are controlled for.

5 Conclusion

Secondo me bisogna scavare nel fatto che gli utenti prezzano a cazzo di cane ma con l'esperienza migliorano

The story:

1. There is an issue on pricing and posting
    - User price better with Experience
    - User with less posts have higher prices (better pricing)
2. People that exert effort price higher
3. People that exert effort has higher probability to sell
4. If we control for reviews and prices, Real Person effect fades
5. For the subset of sold products, exerting an effort reduces time to sell
    - Having the picture of yourself remain significant also when controlling for prices.

Acknowledgements

References

Athey, S., D. S. Karlan, E. Palikot, and Y. Yuan (2022). Smiles in profiles: Improving fairness and efficiency using estimates of user preferences in online marketplaces. *SSRN Electronic Journal*.

Belém, F. M., A. Maros, S. D. Canuto, R. M. Silva, J. M. Almeida, and M. A. Gonçalves (2019). Image aesthetics and its effects on product clicks in e-commerce search. In *eCOM@SIGIR*.

Doleac, J. L. and L. C. Stein (2013). The visible hand: Race and online market outcomes. *The Economic Journal 123*(572), F469–F492.

Edelman, B., M. Luca, and D. Svirsky (2017). Racial discrimination in the sharing economy: Evidence from a field experiment. *American economic journal: applied economics 9*(2), 1–22.

Ert, E., A. Fleischer, and N. Magen (2016). Trust and reputation in the sharing economy: The role of personal photos in airbnb. *Tourism management 55*, 62–73.

Filippas, A., J. J. Horton, and J. M. Golden (2022). Reputation inflation. *Management Science 68*(3), 1714–1735.

Hartmann, S. et al. (2021). Transfer learning for image classification with limited training data. *Journal of Machine Learning 12*(3), 223–245.

Krizhevsky, A., I. Sutskever, and G. E. Hinton (2012). Imagenet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems 25*, 1097–1105.

Kuprashevich, M. and I. Tolstykh (2023). Mivolo: Multi-input transformer for age and gender estimation.

Luca, M. (2017). Designing online marketplaces: Trust and reputation mechanisms. *Innovation Policy and the Economy 17*, 77–93.

Luo, X., B. T. Ratchford, and B. Yang (2008). Consumer evaluations of products: The roles of objective and subjective criteria. *Journal of Consumer Research 34*(5), 778–789.

Ma, X., L. Mezghani, K. Wilber, H. Hong, R. Piramuthu, M. Naaman, and S. Belongie (2019). Understanding image quality and trust in peer-to-peer marketplaces. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)*, pp. 511–520. IEEE.

Olivola, C. Y. and A. Todorov (2010). Elected in 100 milliseconds: Appearance-based trait inferences and voting. *Journal of Nonverbal Behavior 34*(2), 83–110.

Pope, D. G. and J. R. Sydnor (2011). What's in a picture?: Evidence of discrimination from prosper. com. *Journal of Human resources 46*(1), 53–92.

Srivastava, N. et al. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research 15*(56), 1929–1958.

Sun, M. (2012). How does the variance of product ratings matter? *Management science 58*(4), 696–707.

Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics 8*(Volume 8, 2016), 321–340.

Troncoso, I. and L. Luo (2023). Look the part? the role of profile pictures in online labor markets. *Marketing Science 42*(6), 1080–1100.

Watson, J., A. P. Ghosh, and M. Trusov (2018). Swayed by the numbers: the consequences of displaying product review attributes. *Journal of Marketing 82*(6), 109–131.

Zhang, X. et al. (2021). Efficient transfer learning methods for deep neural networks. *IEEE Transactions on Neural Networks 32*(6), 987–999.

Zhang, Y. and X. Luo (2022). Transfer learning in natural language processing and computer vision. *ACM Computing Surveys 55*(2), 1–35.

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

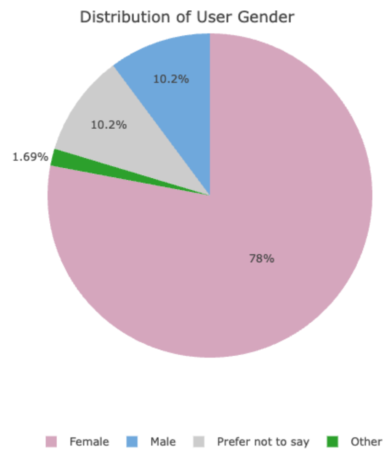

Figure 2: Distribution of User Gender

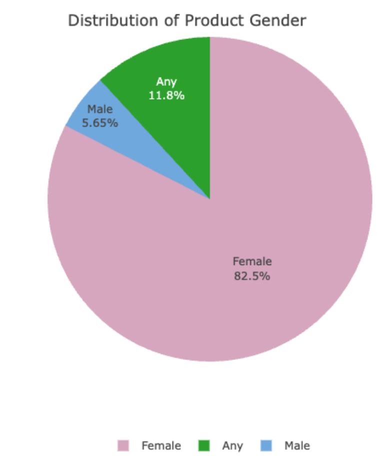

Figure 3: Distribution of Product Gender

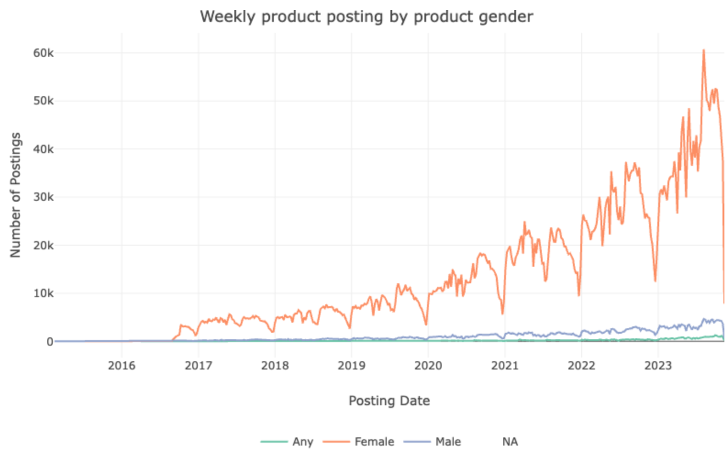

Figure 4: Weekly Product Postings by Product Gender

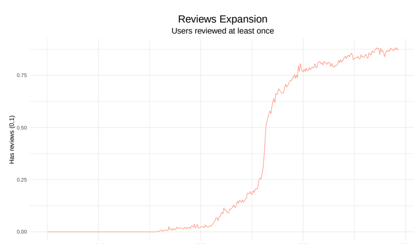

Figure 5: Expansion of User Reviews Over Time

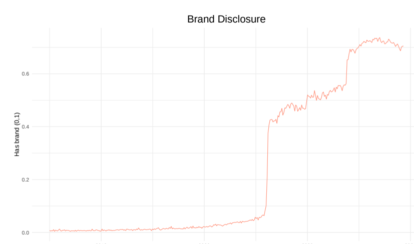

Figure 6: Brand Disclosure Over Time

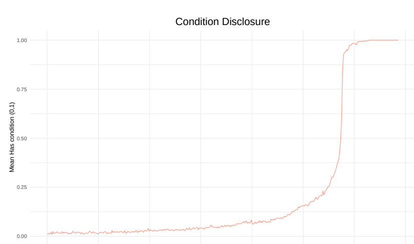

Figure 7: Condition Disclosure Over Time

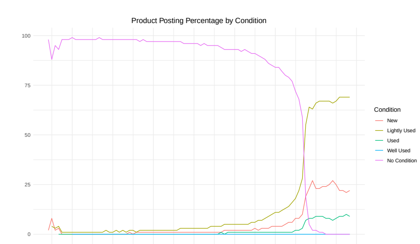

Figure 8: Product Posting Percentage by Condition

Figure 9: Changes in Platform Features Over Time