Picture Perfect? The Impact of Images in Second-Hand Marketplaces

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Abstract

In today's visually-driven world, images play a crucial role in consumer decisions, particularly in the growing second-hand fashion market. This study examines how visual presentation, including personal images, impacts sales performance, on peer-to-peer platforms where sellers act as microentrepreneurs. Focusing on the trade-off between privacy and effective marketing, we analyse product photos based on image type (clothing alone, real person, catalogue image, or professional model) and aesthetics. Regression analyses reveal the importance of visual appeal alongside user experience, reviews, and descriptions in determining marketplace success. Our findings highlight that while experience and reputation matter, professional and personal visuals significantly influence sales outcomes, offering sellers actionable insights to optimize their strategies in a competitive landscape.

JEL Classification Codes: L81, D12, M31, L26.

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1 Introduction

A picture is often said to be worth a thousand words, an idea that resonates strongly within the fashion industry, where visual appeal plays a central role in consumer engagement and purchasing behaviour. Visual appeal, fundamental to human perception, strongly influences purchasing decisions, particularly in second-hand marketplaces. This paper explores how product photos shape buyer behaviour, focusing on the factors that influence sellers' choice of image type and the impact of these choices on sales outcomes.

Second-hand online marketplaces have experienced significant growth in popularity over the past decade. These platforms enable users to buy and sell a wide variety of items, including books, furniture, electronics, and, most prominently, clothing. A notable example is Vinted, which has seen remarkable expansion in recent years. According to Statista (2024), Vinted's revenue grew from $10 million in 2017 to nearly $600 million in 2023. This growth reflects the increasing consumer interest in affordable, sustainable, and convenient shopping alternatives.

The fashion industry thrives on visually showcasing texture, fit, and style, all of which are conveyed instantly through photographs. On peer-to-peer platforms, however, sellers face a unique dilemma: should they include personal images of themselves wearing the items to enhance sales potential? This question highlights the trade-offs between privacy, marketing strategies, and consumer preferences. Sellers must decide how much effort to invest in their listings, balancing the desire to create engaging and professional presentations with the time and resources required to achieve these goals.

This study examines these dynamics through a large-scale observational analysis of second-hand product listings. We investigate how key variables, such as image quality, subject type (e.g., clothing alone, real person, catalogue image, or professional model), and photo aesthetics, influence sellers' decisions and their impact on the likelihood of a sale. Using regression analyses that incorporate user experience, reviews, and descriptions, we uncover the key factors driving success in this competitive marketplace.

Although experience and reputation matter, the visual presentation of products remains fundamental. A seller's choice of image type can significantly impact the perceived value of their product, influencing both buyer engagement and sales outcomes. This study evaluates whether including personal images, even at the potential cost of privacy, can yield higher prices or improved sales performance, providing actionable insights for sellers seeking to optimize their listings.

To explore these dynamics, we utilize data from Tise.com, Norway's largest second-hand marketplace. Our dataset includes over 3 million listings posted between January 2021 and December 2023. Using advanced computer vision techniques, we analyse the first image of each product, which is prominently displayed on the platform's "explore" page and user profiles. Our research addresses two primary questions:

- How do product and user characteristics influence the choice of image type on second-hand online platforms?

- How does the effort invested in product listing pictures affect sales performance?

This study contributes to the growing body of research examining the role of visual presentation in online marketplaces. By focusing on second-hand platforms, we explore how product and user characteristics influence sellers' image choices and their impact on sales outcomes. Our findings advance understanding of how visual appeal shapes buyer behaviour, revealing the nuanced interplay between product presentation, seller reputation, and consumer trust.

In doing so, we extend existing literature on the role of images in online marketplaces, moving beyond established factors like product details and seller reputation to highlight appearance-driven purchasing decisions. Additionally, we contribute to research on marketplace design and reputation systems by examining how photo quality interacts with user feedback to influence buyer trust. Finally, this study builds on work investigating image quality in peer-to-peer platforms by providing new evidence from a large-scale dataset of second-hand listings. The following section reviews the theoretical and empirical foundations of these topics, situating our study within the broader context of research on marketing, e-commerce, and entrepreneurship.

2 Related Literature

Consumer behaviour in second-hand markets is influenced by various factors, including perceived value, environmental consciousness, and economic benefits. These platforms cater to a heterogeneous consumer base ranging from eco-conscious individuals prioritizing sustainability to bargain hunters seeking cost-effective alternatives. This diversity in consumer motivations reflects the broad appeal and varied marketing strategies employed by second-hand marketplaces. For example, platforms like *Vinted*, *Poshmark*, *Depop*, and *Vestiaire Collective* offer tailored features such as social networking elements, product authenticity checks, and a focus on specific niches like luxury or trendy fashion.

A critical aspect of (these) platforms is the reduction of information asymmetries between buyers and sellers. Reputation systems with reviews and ratings (Filippas, Horton and Golden, 2022) play a central role, supplemented by additional features such as profile pictures and bios, which help build trust within the community[1]. These mechanisms align with findings in the literature that both objective criteria (e.g., product descriptions, seller ratings, and price) and subjective criteria (e.g., presentation quality and the inclusion of models) influence consumer decisions (Luo, Kannan and Ratchford, 2008).

Humans are inherently visual creatures (Potter, Wyble, Hagmann and McCourt, 2014), and visual presentation plays a critical role in shaping consumer perceptions in online marketplaces. Previous research high-

[1] Source: Tise.com

lights that product images significantly impact purchasing decisions, often beyond product details or seller reputation (Belém, Maros, Canuto, Silva, Almeida and Gonçalves, 2019). Platforms reinforce this behaviour by recommending best practices for listing photos, such as using natural lighting, highlighting unique features, and modelling the clothing to showcase fit and style[2]. These practices align with broader trends in online engagement, where personal branding and visual storytelling enhance consumer trust and purchasing behaviour (Athey, Karlan, Palikot and Yuan, 2022; Ma, Mezghani, Wilber, Hong, Piramuthu, Naaman and Belongie, 2019).

The presentation of products in second-hand marketplaces is influenced by multiple visual cues that extend beyond basic information. Cleanliness, lighting, and overall aesthetics significantly shape perceptions of quality and desirability. For instance, professionally staged product photos often convey a sense of professionalism and care, influencing consumer trust. These visual elements interact with category-specific expectations; a "vintage-looking" item may appeal to retro fashion enthusiasts while deterring consumers seeking modern styles. This underscores the importance of tailoring product presentation to specific audiences.

In terms of the role of images, research demonstrates that appearance-based perceptions can have significant downstream effects on decision-making (Olivola and Todorov, 2010b). While this is well-documented in domains like politics, where candidate appearance influences voter preferences (Olivola and Todorov, 2010a), similar dynamics are increasingly relevant in e-commerce. In online second-hand marketplaces, presentation quality can drive engagement and sales, yet the interplay between objective and subjective product attributes remains underexplored.

As Troncoso and Luo (2023) analysed, the use of a profile picture is not a straightforward method for building trust in online marketplaces. Instead, other platform design elements, such as reputation systems and product recommendations, play significant roles in shaping user perceptions. In their study of online labour marketplaces for freelancers, they highlight that "looking the part" and demonstrating job fitness are crucial for securing employment. This observation underscores the complexity of appearance-based perceptions, suggesting that visual presentation must align with broader platform mechanisms to effectively influence trust and decision-making.

The role of user-generated photos in building trust is another key focus of existing research. Sellers often act as microentrepreneurs, crafting product "ads" to enhance appeal and visibility. Studies show that personal photos, when aligned with platform design and user preferences, can increase trustworthiness and buyer engagement (Ma et al., 2019). However, this trust-building potential is nuanced. As Troncoso and Luo (2023) argue, the effectiveness of personal imagery depends on its alignment with other platform features like reputation systems and product reviews.

[2]Source: Tise.com Guidelines

Our study contributes to this body of research in three key ways. First, we extend the literature on the influence of images in online marketplaces (e.g., Pope and Sydnor (2011), Doleac and Stein (2013), Edelman, Luca and Svirsky (2017), Ert, Fleischer and Magen (2016), Athey et al. (2022), Troncoso and Luo (2023)) by demonstrating how product photos shape purchasing decisions based on appearance-related perceptions. To our knowledge, this is the first empirical study to explore the role of visual presentation in second-hand marketplaces.

Second, we build on research on online marketplace design and reputation systems (e.g., Sun (2012), Tadelis (2016), Watson, Ghosh and Trusov (2018), Luca (2017)) by examining the interaction between photo quality and user feedback in shaping consumer trust and behaviour.

Finally, we complement findings from Ma et al. (2019) on peer-to-peer marketplaces by showing how image quality and presentation styles influence sales, trustworthiness, and engagement. Our work leverages computer vision techniques to analyse listing photos at scale, offering new insights into the visual dimensions of second-hand markets.

3 Data

This study utilizes data from Tise, a prominent second-hand fashion platform primarily serving the Nordic region, including Norway, Sweden, Denmark, and Finland. Tise facilitates the buying and selling of preowned 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.

3.1 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 behaviours 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 creating a subset, 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, colours, 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.

3.2 Data Description

The data analysed in this study reveals significant gender-based patterns in user demographics and product offerings within the marketplace. The majority of users are female (67.29%), while males constitute 10.09%. Additionally, 21.72% of users prefer not to disclose their gender, and a small minority (1.40%) identify as "Other." Correspondingly, product offerings are predominantly targeted toward females (65.52%). Products labelled as gender-neutral account for 12.61%, while those intended for males represent 4.54%. These trends highlight the marketplace's strong orientation toward female users and products, suggesting potential implications for gender-specific marketing strategies.

Weekly product postings, categorized by target gender, reveal a pronounced and increasing prevalence of female-oriented products from 2020 onward. In contrast, postings for male-oriented, gender-neutral, and unspecified categories have remained relatively stable and significantly lower. This trend underscores a gender skew in the marketplace, suggesting a greater focus on female-oriented products, potentially driven by demand or supply dynamics.

The platform has undergone significant changes over time, particularly in areas such as condition disclosure, brand identification, user reviews, and product condition distribution. These trends suggest that the platform has evolved into a more structured and transparent marketplace.

Descriptive statistics provide an overview of item features such as price, condition, size, and textual attributes. For instance, the majority of items are priced in the lower range, are in "New" or "Lightly Used" condition, and are of size "S". Additionally, caption lengths vary widely, with a significant number of items lacking captions altogether.

Overall, these findings offer a comprehensive view of the platform's user base, product listings, and evolutionary trends. Further details and visual representations can be found in the appendix.

3.3 Developing variables related to images

3.3.1 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 Beauty 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 key points were extracted, including the positions of the nose, eyes, ears, shoulders, elbows, wrists, hips, knees, and ankles. These key points 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.

3.3.2 Labelling the pictures as Homemade Cloth, Real Person, Catalogue Image, Professional Model

The image analysis was conducted using a model trained with YOLOv8 by Ultralytics[4]. 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 analysing 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

[3]CLIP (Contrastive Language-Image Pretraining), is a neural network model developed by OpenAI that can understand and associate images with textual descriptions.

[4]https://www.ultralytics.com

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 labelled 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, Sutskever and Hinton, 2012), and regularization techniques (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.

3.3.3 Image Quality Analysis

For the image quality analysis (IQA), I employed a range of seven objective quality metrics and one combined aesthetics and quality score. The metrics included BRISQUE, NIQE, MUSIQ, DBCNN, PAQ, PIQE, and IL-NIQE, each evaluating distinct aspects of image fidelity and aesthetic appeal. Together, these metrics provide a comprehensive framework for assessing the quality of product images in the dataset[5].

In addition to these metrics, a subset of 15,000 images was analysed using the Q-Align Score (Wu, Zhang, Zhang, Chen, Li, Liao, Wang, Zhang, Sun, Yan, Min, Zhai and Lin, 2023), which integrates aesthetics and quality evaluations into two comprehensive measures. Q-Align is particularly valuable for analysing the alignment between image quality and aesthetic appeal, offering a holistic perspective on how visual presentation impacts consumer perceptions. The Q-Align scores from this subset were then used to train a machine learning model, specifically a random forest, to predict Q-Align scores across the entire sample.

[5]Further information on the scores can be found in the Appendix 7.2

4 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*, *Catalogue image*, *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 choice of picture of the listing. This analysis employs a logistic regression model to explore how product characteristics, seller reputation, and, critically, the person category of the first image, impact the price-setting behaviour of sellers.

Second, we assess the likelihood of a product being sold, using again a logistic model. The binary outcome (whether the product sells) is modelled as a function of pricing, 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.

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

4.1 The Models

4.1.1 Image Choice

$$
\begin{aligned}
\text{Image Choice}_{i,j,t} = \alpha_i + \beta_0 \cdot \text{Product Characteristics}_i + \beta_1 \cdot \text{Ad Characteristics}_i + \beta_2 \cdot \text{Price}_i \\
+ \beta_3 \cdot \text{User Reputation and Experience}_j + \beta_4 \cdot \text{Brand Reputation}_{j,t} \\
+ \beta_5 \cdot \chi_{i,j} + \varepsilon_{i,j,t}
\end{aligned} \tag{1}
$$

To examine the factors influencing the choice of image category in product listings, I employ a logistic regression model. The logistic regression model also supports the inclusion of Fixed Effects (FE), allowing for control of unobserved heterogeneity across product categories.

The model structure accounts for various predictors influencing image choice, including product characteristics, listing features, price tier, user reputation and experience, and brand reputation. These predictors capture the key dimensions that may shape sellers' decisions regarding the type of image to use, whether professional, self-taken, or featuring a person. The other controls further refine the analysis.

By incorporating Fixed Effects, the logistic regression model effectively controls for unobserved characteristics specific to categories, such as jackets, dresses, or pants, which might influence image selection. This ensures that the analysis isolates the effects of the included predictors on image choice, without being confounded by unmeasured category-level variation.

The logistic regression approach provides interpretable estimates of the factors associated with different image categories. This aligns with the study's objective of understanding how sellers decide on the presentation of their products in second-hand marketplaces.

4.1.2 How does image category affect purchasing choices?

To examine how image category influences the likelihood of a product being sold, I employ a logistic regression model. Logistic regression is well-suited for binary outcomes, such as the choice of image category or sale occurrence, providing robust estimates of the relationship between predictors and the dependent variable. Additionally, it allows for the inclusion of Fixed Effects (FE), enabling control for unobserved heterogeneity across categories.

Using a logistic regression model, the analysis provides interpretable estimates of how predictors relate to the probability of a sale. The focus on image category allows for an exploration of how different types of visuals, such as professional or self-taken images, contribute to the perceived value and attractiveness of a listing. The use of Fixed Effects ensures that these estimates are not biased by unobserved differences across categories.

This approach aligns with the study's objective of understanding the determinants of successful sales and provides robust insights into the role of image category in influencing buyer behaviour.

$$\begin{aligned}\text{Sale Outcome}_{i,j,t} = {} & \alpha_i + \beta_0 \cdot \text{Picture Category}_i + \beta_1 \cdot \text{Product Characteristics}_i + \beta_2 \cdot \text{Ad Characteristics}_i \\ & + \beta_3 \cdot \text{Price}_i + \beta_4 \cdot \text{User Reputation and Experience}_j + \beta_5 \cdot \text{Brand Reputation}_{j,t} \\ & + \beta_6 \cdot \chi_{i,j} + \varepsilon_{i,j,t}\end{aligned} \tag{2}$$

Further details can be found in the appendix 7.2

5 Results

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

5.1 Drivers of image choice

In the following section, I will show the drivers that make users select a level of effort in choosing the picture type when creating an ad on the platform.

These picture types, ranging from homemade pictures of the cloth and images featuring a real person to catalogue images and professional model photos, are influenced by variables such as price quintile, product characteristics, brand perception, and seller activity metrics. The results, presented in Table **??**, for the full sample reveal a strong association between higher price quintiles and the use of professional-grade pictures (catalogue and model). This indicates that sellers are more likely to invest in polished visuals for higher-value items, aligning their strategies with perceived buyer expectations. An additional noteworthy finding is the strong negative association between prices and the use of homemade images, contrasted with a smaller but positive association with images featuring a real person.

We can visualize specific results for all categories analysed, sweaters, tops, pants, dresses and jackets, in Appendix from Table A.6 to A.10.

Across all categories analysed, there is a strong and consistent association between higher price quintiles and the choice of professional-grade images, specifically cloth professional and person professional. This pattern indicates that sellers strategically invest in polished visuals for higher-value items, aligning their presentation with buyers' expectations for premium products. In contrast, lower price quintiles are more frequently associated with more accessible image choices, such as using a self-portrait or taking a photo of the garment at home, reflecting a reduced level of seller effort for lower-value items.

The beauty category is another important determinant influencing picture choice. Across all categories, items with higher beauty scores are more likely to feature their own image. This suggests that sellers recognize the value of leveraging aesthetic appeal through their image presentation. Although the magnitude of the beauty category's effect is smaller than that of price quintiles, it remains statistically significant and consistent across product types, reinforcing the importance of visual aesthetics in influencing picture choice.

It is noteworthy that when sellers choose not to disclose the condition of the garment, they are more likely to use professional catalogue images. This behaviour suggests a potential attempt to avoid featuring the actual item in the first picture, possibly to obscure the garment's true condition.

5.2 Sales outcomes

The results of the logistic regression provide valuable insights into how different image types, Real Person, Catalogue Image, and Professional Model, affect the likelihood of a product being sold, compared to a baseline of informal, homemade pictures taken in a domestic setting that do not feature any of these characteristics. While the full sample analysis does not reveal significant effects for these variables, breaking down the data by product category uncovers distinct patterns. These findings highlight the nuanced role of image presentation in driving sales and underscore the importance of tailoring visual strategies to align with category-specific buyer preferences. Below, the results are discussed in greater detail.

On the full sample, as aforementioned, the variables for Real Person, Catalogue Image, and Professional

Model do not show significant results, suggesting limited or no clear patterns when all categories are analysed together. However, when the sample is split into individual categories, distinct patterns begin to emerge. For Real Person images, the results vary by category. In dresses, this image type has a strong and significant positive association with sales, indicating that showcasing fit or style on a real person enhances buyer interest in this category. In contrast, sweaters and pants show significant negative associations, suggesting that buyers may prefer professional or product-only visuals for these items. Catalogue Images consistently demonstrate a significant and positive association with sales across most categories, including dresses, tops, and jackets. This highlights the effectiveness of polished, professional product displays in appealing to buyers. The strong positive effect in dresses and jackets, in particular, suggests that these image types align well with buyer expectations for clarity and quality in visual presentation. Professional Model images show notable positive effects in categories such as dresses and jackets, where this image type significantly enhances sales likelihood. However, in other categories like pants, the effect is not significant, indicating that professional model images may be less impactful for items where fit and style are less critical to buyer decisions. These category-specific patterns underscore the varying effectiveness of image types depending on the product being sold, emphasizing the importance of tailoring image presentation to align with buyer preferences for each category.

The results highlight a positive and significant association between higher price quintiles and the probability of a sale across all categories. The effect size increases consistently from the second to the fifth quintile, with the highest quintile exhibiting the strongest effect. For instance, in the full sample, the coefficients of the second, third, fourth, and fifth quintiles, with respect to first quintile, are 0.067, 0.210, 0.361, and 0.548, respectively, with similar patterns observed across individual categories.

The variable capturing whether the garment's condition is disclosed *Condition Disclosed* is negatively associated with sales in several categories, including pants and jackets, which may indicate buyer scepticism or reduced trust when condition details are provided.User-related factors play a crucial role in predicting sales outcomes. The number of reviews at the time of purchase consistently shows a positive and significant association with sales across all categories, highlighting the importance of a strong reputation in influencing buyer decisions. Similarly, the number of likes on a listing emerges as a significant predictor of sales, underscoring the role of engagement and perceived popularity in enhancing a product's appeal to potential buyers. Both factors collectively emphasize the impact of user reputation and listing engagement in driving successful sales.

Brand-related factors, such as brand perception and the log of brand products, show nuanced effects. Brand perception positively influences sales across most categories, with the strongest effects seen in dresses and jackets. The log of brand products is positively associated with sales in the full sample but exhibits mixed effects when disaggregated by category, probably due to the reduction of size for brands when using individual categories.

The variables for Beauty and Person in Profile Picture[6], reveal interesting patterns in the data. Beauty, which captures the aesthetic appeal of the user, consistently shows a small but significant negative association with sales across all categories. This suggests that higher beauty ratings, while visually appealing, may introduce scepticism among buyers or indicate products with less practical appeal. In contrast, the presence of a person in the seller's profile picture has a consistently positive and significant association with sales across all categories. This finding underscores the importance of trust and relatability in online marketplaces, as buyers may perceive sellers with personal profile pictures as more trustworthy or approachable, thereby increasing the likelihood of completing a purchase.

5.3 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 A.22 and A.23, both for unique users and generally across all users who post products on the platform. The variable *Beauty Category* was constructed by dividing the beauty scores into 10 equal intervals, each representing a 10-point range within the 0-100 scale. This categorization creates a straightforward way to group items based on their aesthetic appeal, with categories ranging from 0-10 (lowest beauty) to 90-100 (highest beauty). By using this categorical representation, the analysis captures the effect of varying levels of perceived beauty on sales outcomes while facilitating the interpretation of interactions with image type.

The results in Table A.5 highlight the nuanced relationship between beauty, image type, and the likelihood of a product being sold. Overall, the *Beauty Category* exhibits a small yet consistent negative association with sales across all specifications. For example, in the full sample, a one-unit increase in the beauty score is associated with a 0.002 percentage point decrease in the likelihood of a sale. This negative relationship persists across all product categories, suggesting that while beauty might initially attract attention, it does not consistently translate into higher sales.

When considering image types, *Real Person* images show mixed results across categories. For instance, they have a significant positive effect in the dresses category, with a strong association between this image type and sales. However, in other categories such as sweaters, pants, and jackets, *Real Person* images exhibit significant negative effects, indicating that less professional imagery may detract from buyer confidence in these segments.

Catalogue Images, by contrast, generally display positive and significant effects on sales, particularly in cat-

[6] How beauty is calculated will be covered in detail in the next section

egories such as tops, dresses, and jackets. For dresses, the use of catalogue images is associated with a substantial increase in sales likelihood, reflecting buyers' preference for polished and professional presentation in this category. Similarly, *Professional Model* images yield significant positive results for dresses and jackets, where their use aligns with buyer expectations for premium items. However, in some categories such as sweaters and pants, the results for professional images are weaker or non- significant, indicating that the value of this presentation style may vary depending on the type of product.

The interaction terms further emphasize the complex role of beauty in these relationships. For example, the interaction between *Beauty Category* and *Catalogue Image* shows positive effects in sweaters, pants, and jackets, suggesting that catalogue images enhance the value of visually appealing products in these categories. Similarly, the interaction between *Beauty Category* and *Professional Model* is positive and significant for dresses and jackets, reinforcing the importance of professional presentation for high-beauty items.

Finally, having a *Person in Profile Picture* consistently shows a positive and significant association with sales across all categories. This finding underscores the importance of seller trust and relatability in driving sales outcomes. Together, these results highlight the interplay between beauty, image type, and perceived professionalism in shaping buyer behaviour across different product categories.

5.3.1 Heterogeneity

The heterogeneity test results presented in Table A.11 offer valuable insights into how the interaction between beauty and image type influences the likelihood of a product being sold across different subsamples. The analysis is segmented into four groups: the bottom 100,000 observations ranked by beauty score, the top 100,000 observations, all the other observations with a recorded beauty score, and those without a profile picture. This segmentation enables a detailed exploration of the interplay between beauty and image presentation under varying conditions, shedding light on how these factors contribute to sales performance.

In the bottom beauty category, the *Real Person* image type has a significant negative association with sales (-0.271), suggesting that personal imagery might detract from buyer confidence in lower-beauty listings. However, the interaction term (*Beauty* × *Real Person*) is positive and significant (0.010), indicating that as beauty increases within this subsample, the negative impact of real-person images diminishes.

For products in the top beauty category, the results are more pronounced. Here, *Real Person* images exhibit a strong negative effect (-1.03), emphasizing that buyers of highly attractive items may expect professional presentations. This is further supported by significant positive interactions for *Beauty* × *Real Person* (0.014) and *Beauty* × *Catalogue Image* (0.012), suggesting that higher beauty scores amplify the value of more polished image types. Interestingly, the interaction term for *Beauty* × *Professional Model* is not significant, implying that beauty and professional model imagery operate independently in this group.

For items in the middle beauty ranges, the patterns are less extreme but still significant. *Real Person* images have a negative effect (-0.179), while *Catalogue Image* and *Professional Model* both show positive associations (0.089 and 0.200, respectively). This suggests that polished visuals are effective across moderate beauty levels, with professional images having a particularly strong impact.

Finally, in the no-profile-picture group, *Real Person* images have a positive effect (0.053), contrasting with the other groups. This result suggests that in the absence of seller-specific information, such as a profile picture, personal imagery may serve as a proxy for trustworthiness or authenticity.

Overall, these results underscore the nuanced interplay between beauty, image type, and sales outcomes. The findings highlight the varying roles of professionalism and trust signals across different beauty levels, suggesting that sellers should carefully tailor their image strategies based on the aesthetic characteristics of their products and their own profile features.

6 Conclusion

This study investigates the impact of image categories on posting behaviour and sales performance within the second-hand fashion marketplaces, 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, the use of a *Real Person* in product images exhibits mixed effects. While it shows a modest positive influence on sales probability in some categories, it generally performs less effectively compared to professional-grade images such as *Catalogue Image* and *Professional Model*. Interestingly, in certain high-beauty items, the interaction between *Real Person* images and appearance scores offsets some of the negative effects, indicating nuanced buyer preferences in these cases.

For sales performance, *Catalogue Image* and *Professional Model* categories consistently enhance the likelihood of a sale across most product categories, reinforcing the importance of professional and aesthetically pleasing presentations. The interaction between beauty and these professional image categories further amplifies their effectiveness in categories like dresses and jackets, where style and fit are particularly important. These findings underscore the dominance of professional-grade visuals in driving consumer trust and product desirability.

The *Beauty Category* variable introduces another layer of complexity. While higher beauty scores are generally associated with a slight negative effect on the likelihood of a sale, interactions with professional image types suggest that beauty enhances the impact of polished visuals. This relationship highlights that professional presentation can complement but not entirely substitute the effects of product aesthetics. Additionally, having a *Person in Profile Picture* consistently shows a positive association with sales across all categories, emphasizing the role of perceived trustworthiness and relatability in online marketplaces.

Overall, this study underscores the critical role of visual presentation in online marketplaces. Sellers who invest in professional-grade imagery can enhance their pricing power, sales performance, and market appeal, especially when targeting premium segments. Future research could delve deeper into the interactions between beauty, image presentation, and other listing attributes, such as descriptive text and pricing strategies, to uncover a more holistic understanding of consumer behaviour in second-hand markets. Expanding this analysis to other platforms and product categories could further validate and generalize these findings, offering actionable insights for sellers and marketplace designers alike.

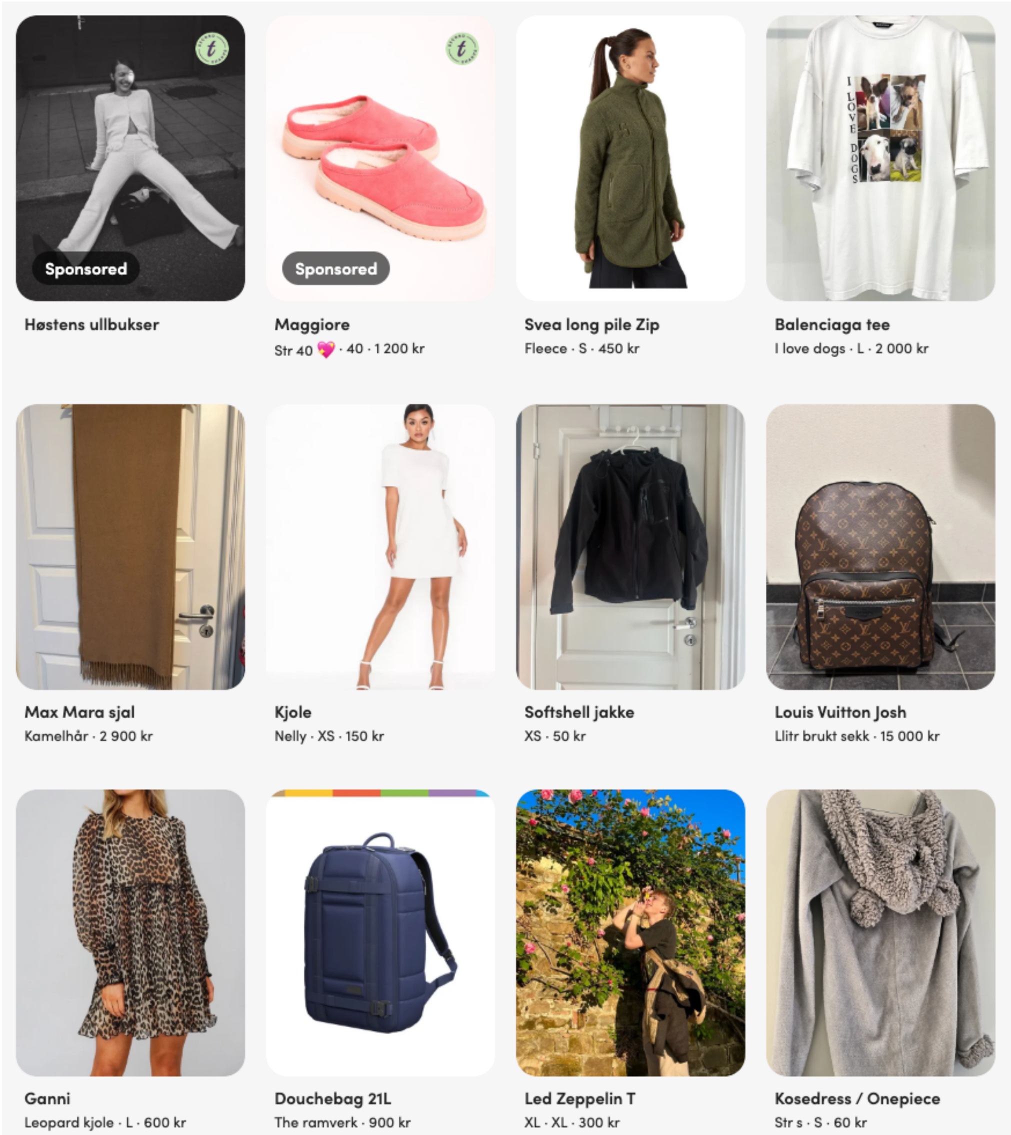

Figure 1. Website interface

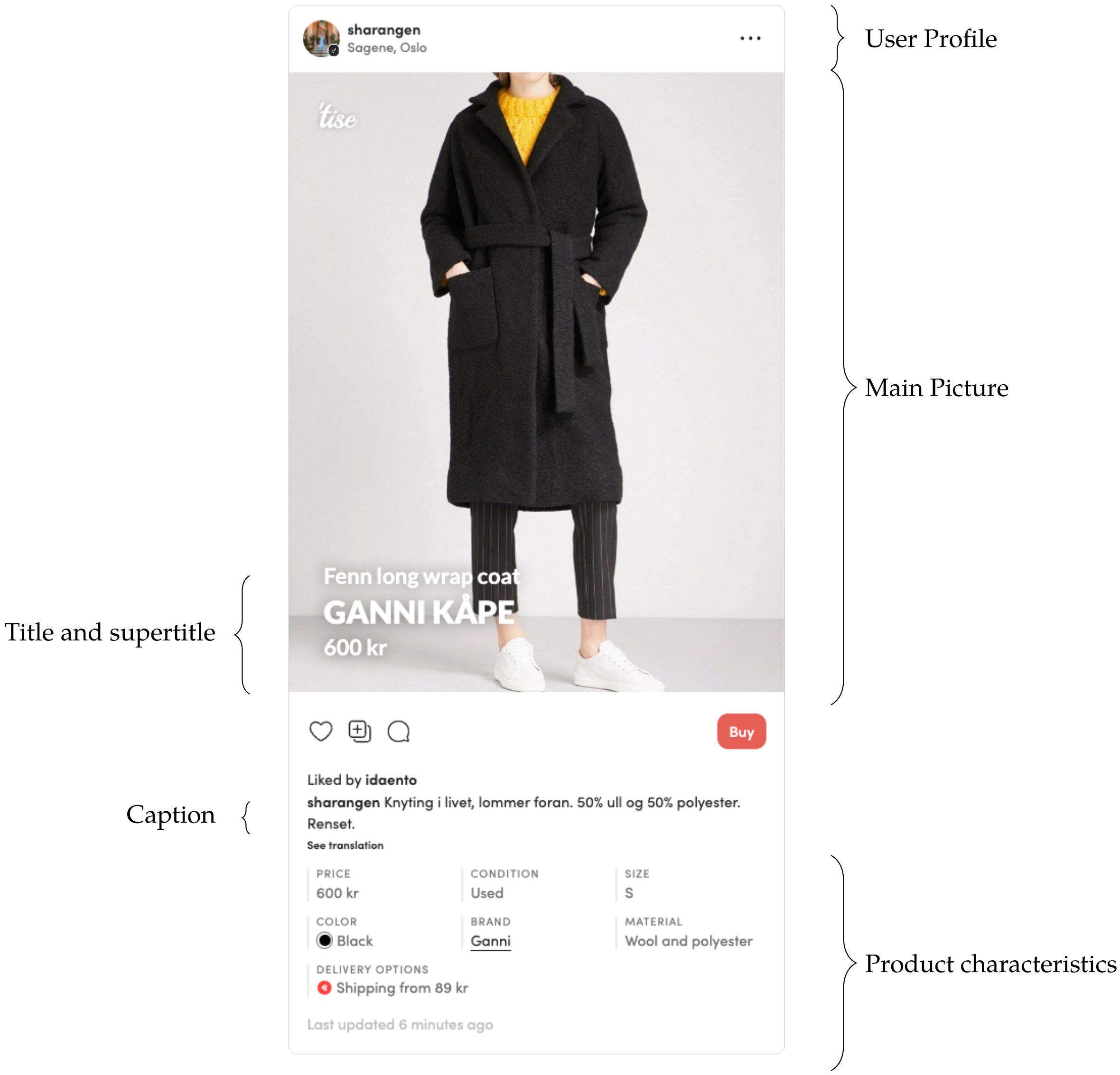

Figure 2. Ad sample

7 Appendices

Tables and Figures

Products

Informal setting without person

Catalog Image setting without person

Informal setting with person

Catalog Image with person

Figure A.1. Examples of product display

Data Description

Table A.1. Summary Statistics for continuous variables

Variable	Mean, Std. Dev.	25^{th}, 50^{th}, 75^{th} Percentiles	Min - Max	N
Product Characteristics				
Price (in NOK)	341.37, 452.47	100.00, 200.00, 400.00	1.00 - 4,999.00	3,048,284
Number of Likes	8.11, 16.08	2.00, 4.00, 9.00	0.00 - 1,658.00	3,048,284
Number of Images	2.79, 1.16	2.00, 3.00, 4.00	1.00 - 9.00	3,048,284
Product Title length	12.14, 4.47	9.00, 12.00, 16.00	2.00 - 49.00	3,048,284
Product Caption length	112.10, 107.18	44.00, 87.00, 148.00	0.00 - 3,223.00	3,048,284
Profile Picture Variables[1]				
Age	29.41, 8.36	23.42, 28.19, 34.46	0.31 - 83.07	2,568,641
Number of Faces	1.04, 0.51	1.00, 1.00, 1.00	0.00 - 21.00	2,568,641
Number of People	1.19, 0.63	1.00, 1.00, 1.00	0.00 - 25.00	2,568,641
Percent of pixels occupied by the face	11.06, 11.28	2.94, 6.90, 16.32	0.05 - 99.60	2,358,685
Beauty	53.72, 15.16	42.25, 53.41, 64.88	9.06 - 96.19	2,568,641
Percentage of Head Keypoins present	77.15%, 19.56%	80.00%, 80.00%, 80.00%	0.00% - 100.00%	2,568,641
Percentage of Upper Body Keypoins present	45.94%, 34.86%	16.67%, 33.33%, 66.67%	0.00% - 100.00%	2,568,641
Percentage of Lower Body Keypoins present	15.57%, 29.14%	0.00%, 0.00%, 33.33%	0.00% - 100.00%	2,568,641
Reputation Variables				
Number of Reviews at Posting	13.89, 26.33	1.00, 5.00, 16.00	0.00 - 894.00	3,048,284
Average Rating at Posting	4.99, 0.12	5.00, 5.00, 5.00	1.00 - 5.00	2,445,812
Number of Reviews at Purchase	18.01, 30.43	2.00, 8.00, 21.00	0.00 - 1,014.00	3,048,284
Average Rating at Purchase	4.99, 0.11	5.00, 5.00, 5.00	1.00 - 5.00	2,714,364
Number of Products Posted	58.71, 85.62	12.00, 29.00, 68.00	1.00 - 973.00	3,048,284
Number of Products Sold	45.32, 73.29	7.00, 20.00, 52.00	0.00 - 953.00	3,048,284
Additional Variables				
Days to Sell	107.45, 168.42	2.06, 27.63, 144.61	0.00 - 1,181.60	3,048,284

[1]Conditional on having a person in the profile picture.
Price selected between 1 and 5000 Norwegian Kronas

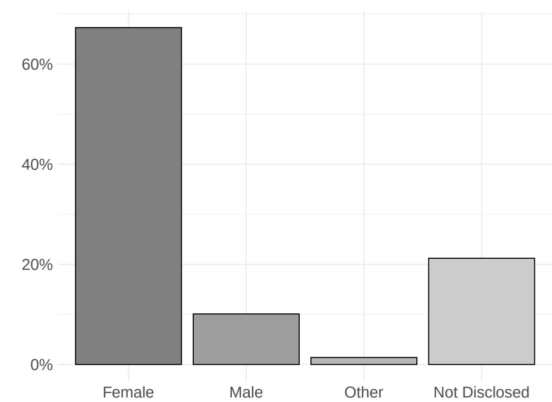

Figure A.2. User-Reported Gender Distribution of Accounts

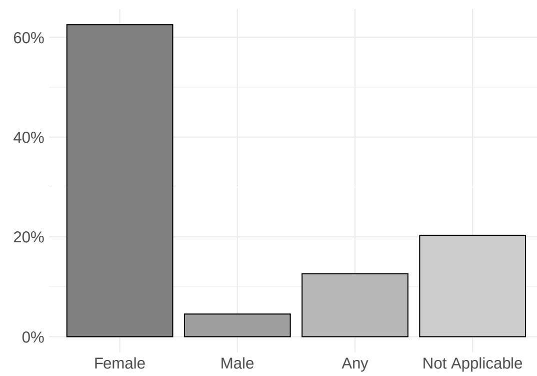

Figure A.3. User-Reported Gender Distribution of Products

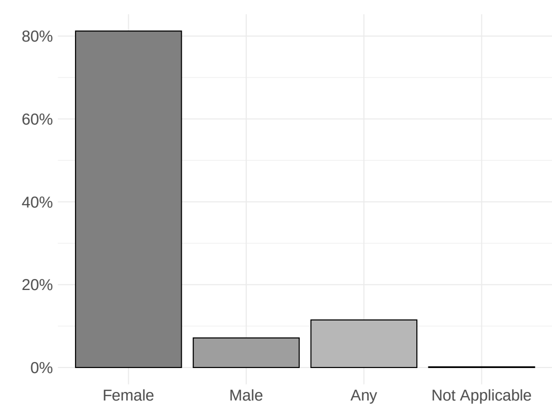

Figure A.4. User-Reported Gender Distribution of Products (Clothes Only)

Descriptive Statistics - Maps

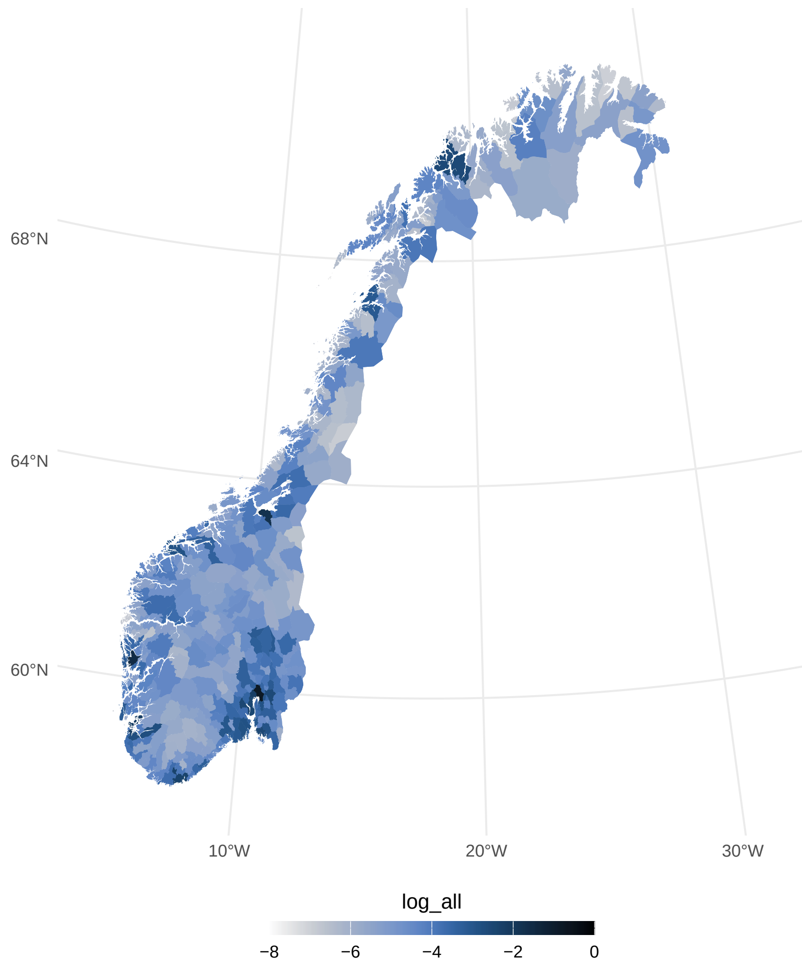

Figure A.5. Users across Norway

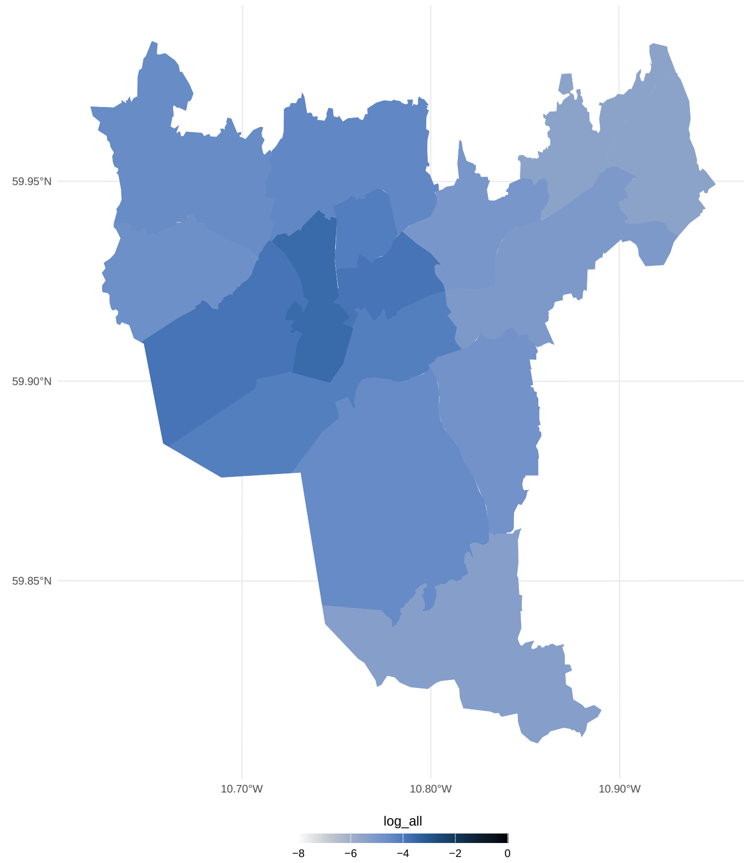

Figure A.6. Users in the Capital city, Oslo

Descriptive Statistics - Over Time

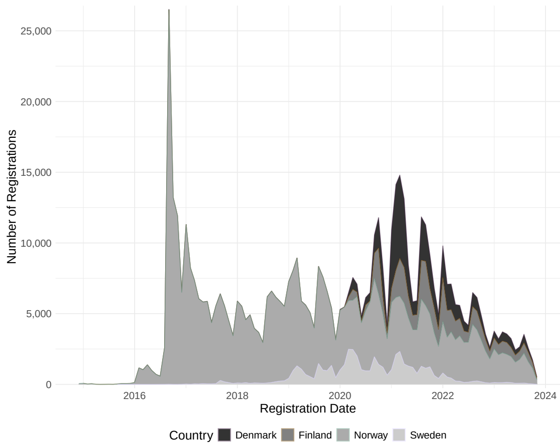

Figure A.7. Monthly User Registrations by Country

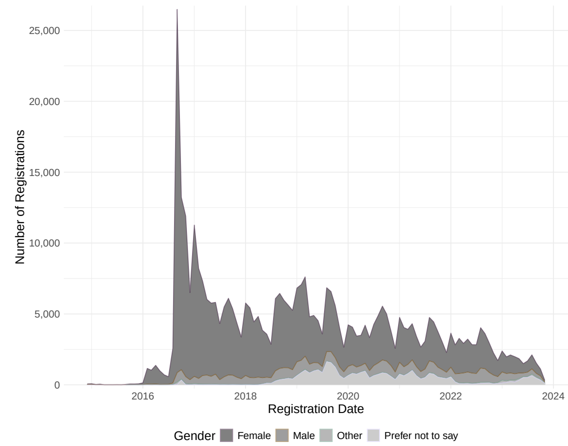

Figure A.8. Monthly User Registrations by Gender in Norway

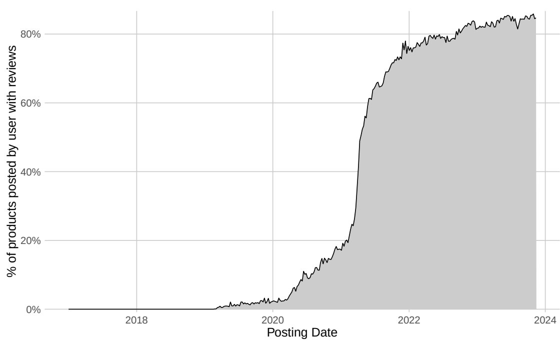

Figure A.9. Expansion of User Reviews Over Time

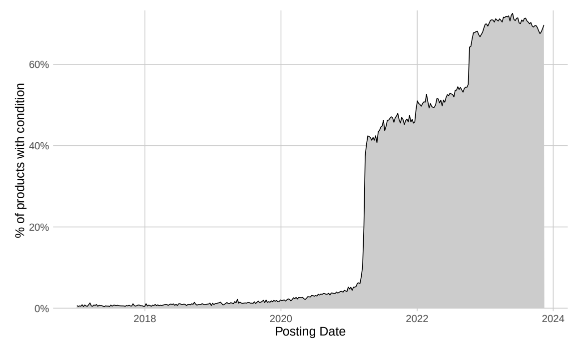

Figure A.10. Brand Disclosure Over Time

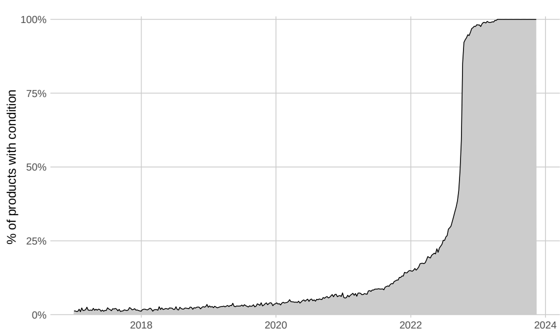

Figure A.11. Condition Disclosure Over Time

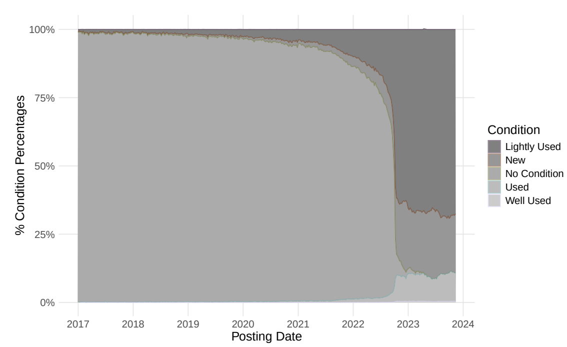

Figure A.12. Product Posting Percentage by Condition

Figure A.13. Changes in Platform Features Over Time

Descriptive Statistics - Plots

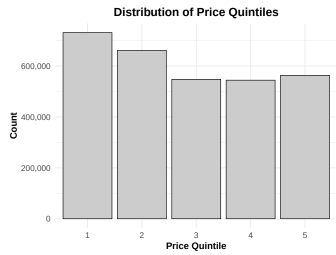

Figure A.14. Quintiles are calculated per category, per month, and show the frequency distribution of items across quintiles 1 to 5.

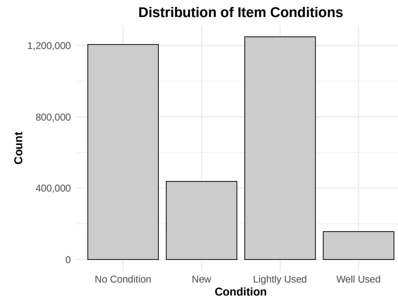

Figure A.15. Conditions include categories such as "No Condition," "New," "Lightly Used," and "Well Used."

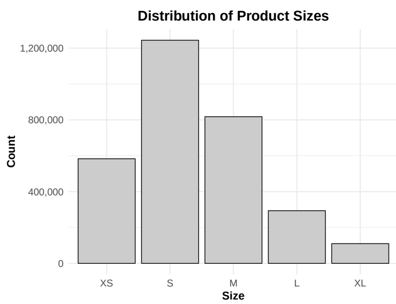

Figure A.16. Product Sizes are categorized as XS, S, M, L, and XL.

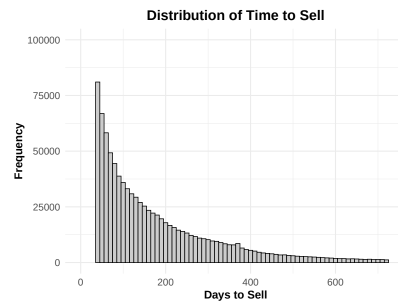

Figure A.17. This histogram shows the number of days it took to sell items, capped at 730 days (2 years).

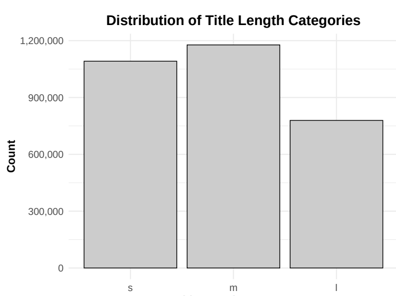

Figure A.18. Title lengths are divided into bins: "s" (0-10 characters), "m" (11-15 characters), and "l" (16+ characters).

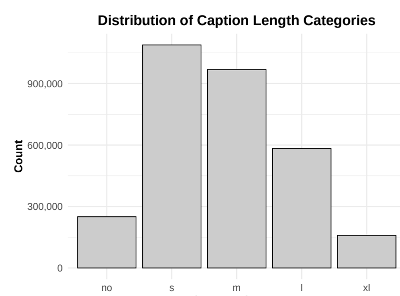

Figure A.19. Categories include: "no" (0 characters), "s" (1-75), "m" (76-150), "l" (151-300), and "xl" (301+ characters).

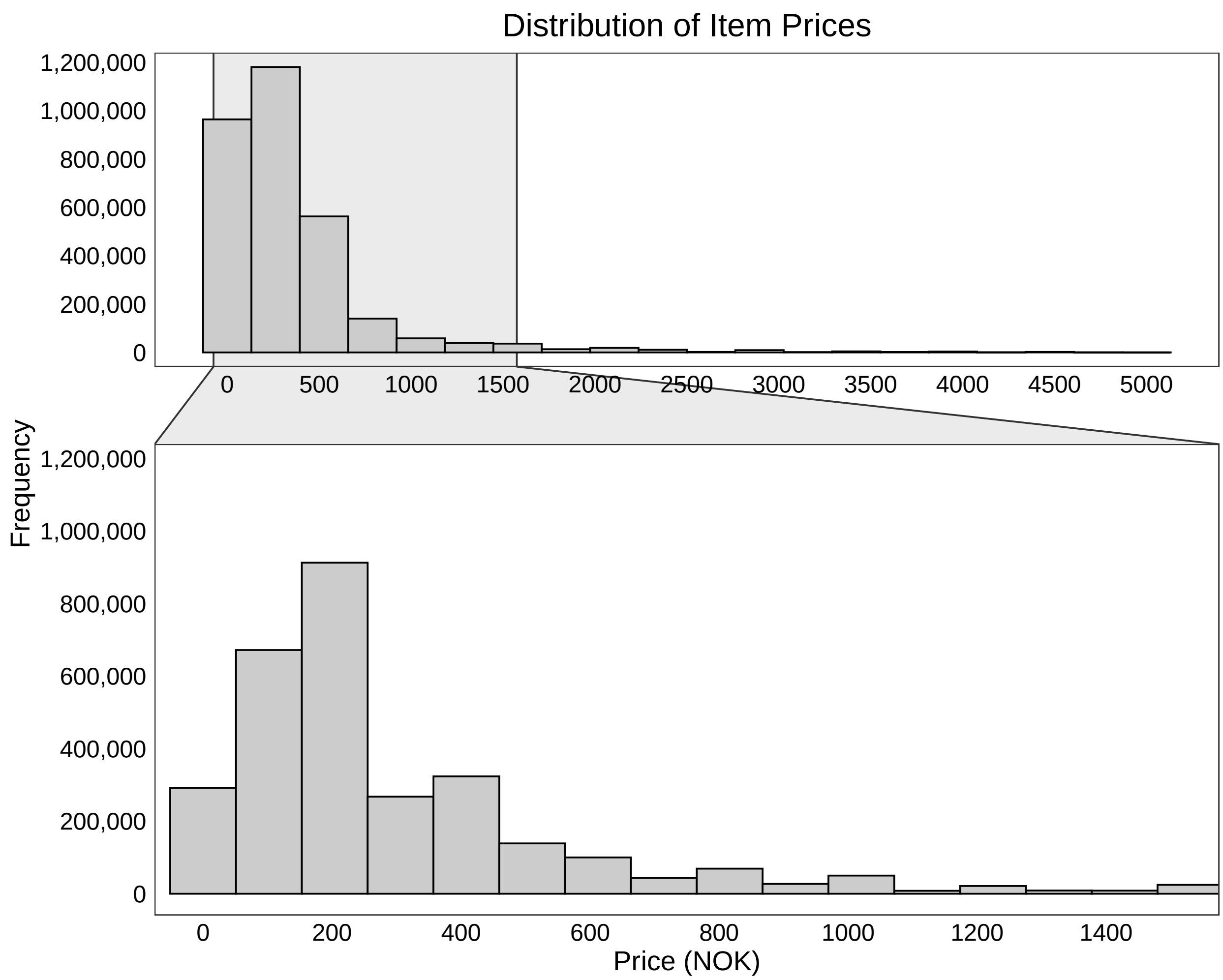

Figure A.20. The histogram shows the distribution of item prices rounded to the nearest NOK 10.

Image Classification Training

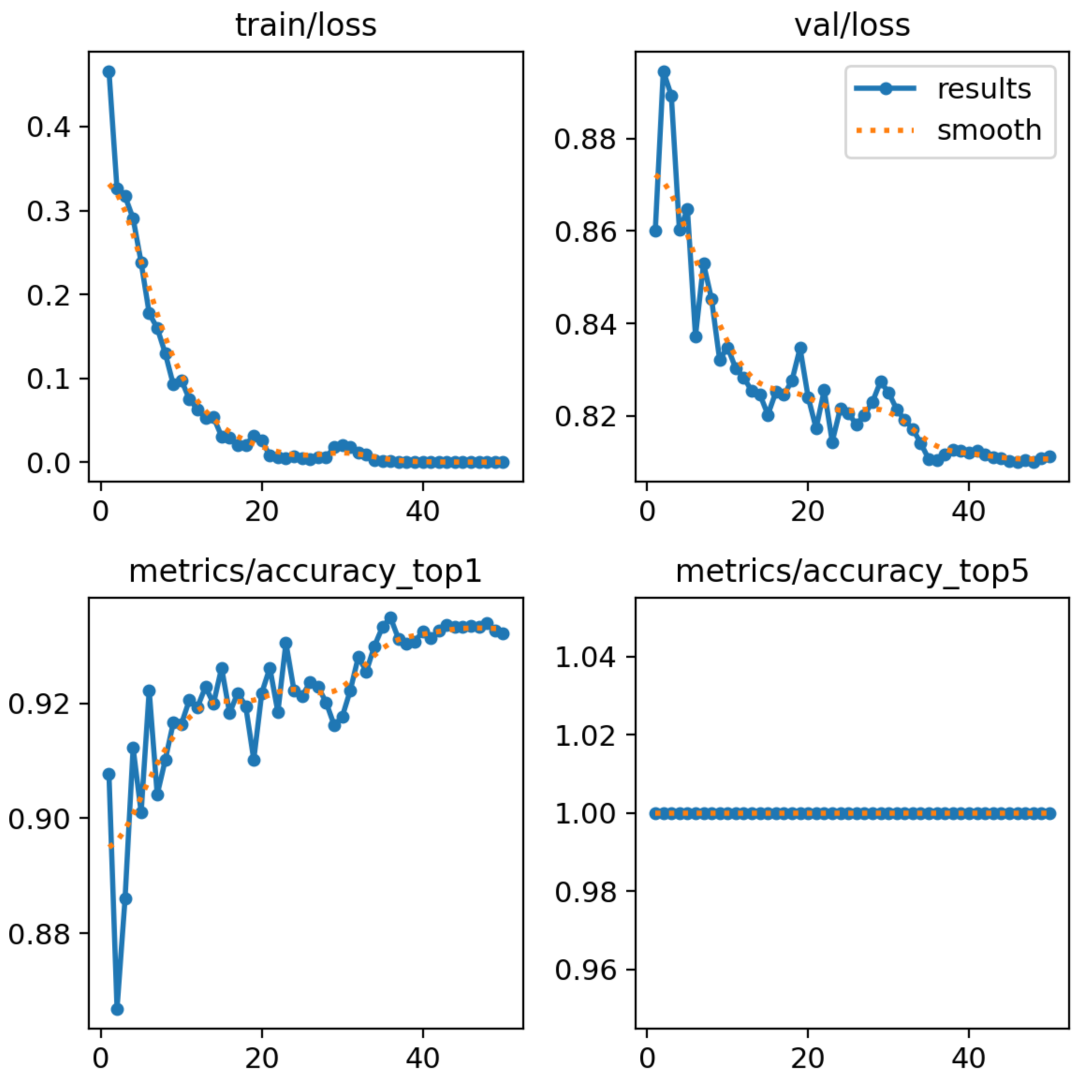

Figure A.21. Training Results

Beauty

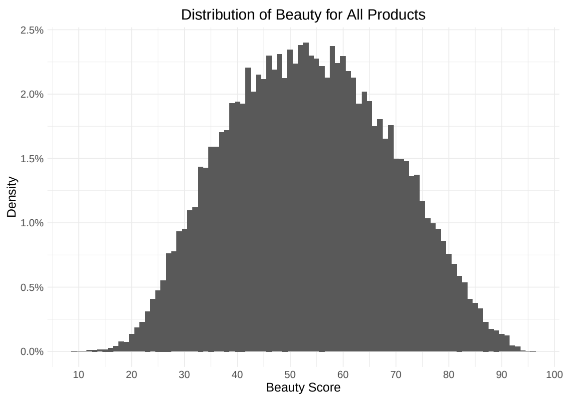

Figure A.22. Distribution of beauty per product

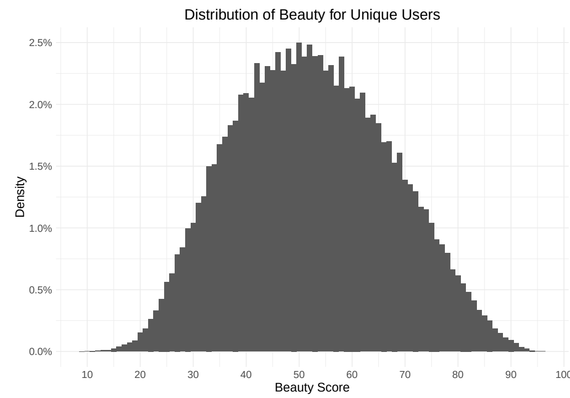

Figure A.23. Distribution of beauty per user

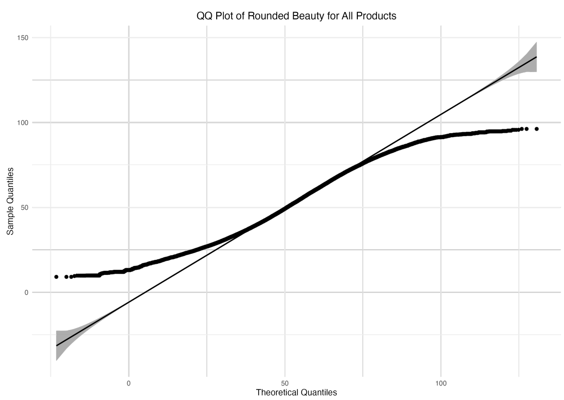

Figure A.24. QQ Plot of Beauty Score for All Products

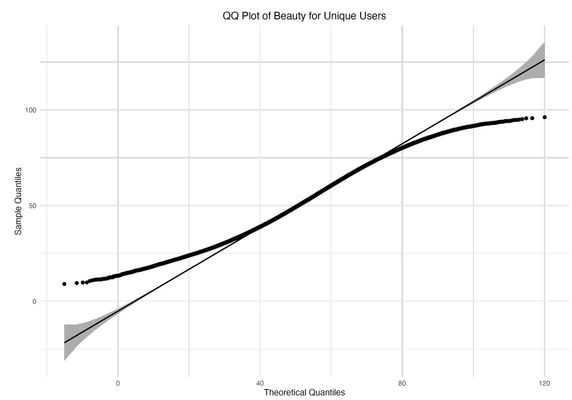

Figure A.25. QQ Plot of Beauty Score for unique Users

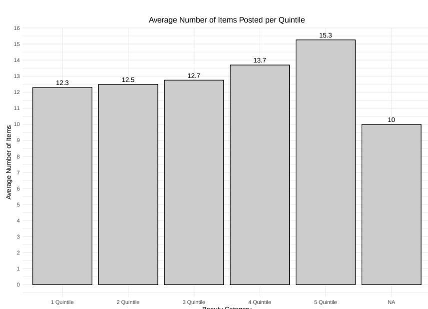

Figure A.26. Average number of item posted per Beauty Category.

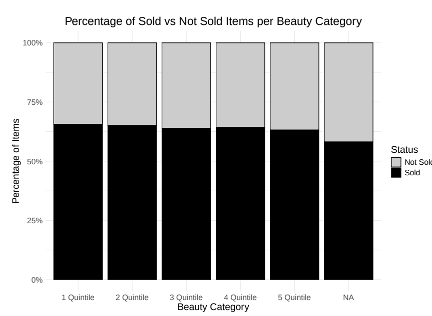

Figure A.27. Percentage of item sold per Beauty Category.

Results

7.1 Main Results

Table A.2. Logistic Regression on Picture Type choice for All Products

Dependent Variables:	Homemade Image	Real Person	Catalogue Image	Professional Model
Category	Full sample			
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.948***	0.188*	0.714***	0.952***
	(0.169)	(0.104)	(0.132)	(0.107)
Condition Disclosed	0.150***	-0.033	-0.032	-0.159**
	(0.038)	(0.042)	(0.084)	(0.072)
Log(1 + Reviews at Posting)	-0.200***	0.100***	0.105***	0.148***
	(0.012)	(0.015)	(0.015)	(0.008)
Log(1 + (Posted - Sold))	0.038	0.068***	-0.071***	-0.112***
	(0.030)	(0.019)	(0.011)	(0.015)
Log(Posted)	0.060*	-0.054*	-0.079**	0.004
	(0.035)	(0.029)	(0.025)	(0.009)
Beauty	-0.021***	0.016***	0.002***	0.011***
	(0.001)	(0.0004)	(0.0006)	(0.001)
Number of Images	-0.019	0.071**	-0.233***	0.045
	(0.027)	(0.029)	(0.020)	(0.036)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors	Category			
Observations	789,047	789,047	789,047	789,047
Squared Correlation	0.140	0.056	0.032	0.079
Pseudo R^2	0.106	0.049	0.051	0.085
BIC	978,477.4	850,396.6	379,858.9	684,161.1

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalogue Image, and Professional Model. The regression includes the full sample with 5 product categories and a total of 789,047 observations. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Logist Regresssion Sold (0/1)

Dependent Variable:	Sold Outcome (0/1)					
Category	Full sample	Sweaters	Tops	Pants	Dresses	Jackets
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Price Quintile: Linear	0.440***	0.520***	0.507***	0.343***	0.360***	0.457***
	(0.041)	(0.013)	(0.017)	(0.013)	(0.011)	(0.015)
Price Quintile: Quadratic	0.066***	0.068***	0.199***	0.014	0.071***	0.033***
	(0.022)	(0.011)	(0.015)	(0.012)	(0.010)	(0.013)
Price Quintile: Cubic	-0.013	-0.014	0.052***	-0.072***	-0.0002	-0.016
	(0.017)	(0.012)	(0.015)	(0.011)	(0.009)	(0.013)
Condition Disclosed	-0.168**	-0.091	0.176	-0.306**	-0.107	-0.446***
	(0.081)	(0.097)	(0.160)	(0.119)	(0.104)	(0.130)
Real Person	0.043	-0.115***	-0.021	-0.137***	0.358***	0.011
	(0.112)	(0.013)	(0.017)	(0.013)	(0.011)	(0.015)
Catalog Image	0.200**	0.107***	0.360***	-0.059***	0.344***	0.216***
	(0.078)	(0.020)	(0.026)	(0.022)	(0.019)	(0.020)
Professional Model	0.229	0.059***	0.083***	-0.005	0.589***	0.181***
	(0.143)	(0.018)	(0.020)	(0.013)	(0.012)	(0.019)
Beauty	-0.001***	-0.0009**	-0.001***	-0.0007*	-0.001***	-0.002***
	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0004)
Person in Profile Picture	0.107***	0.111***	0.112***	0.101***	0.108***	0.141***
	(0.007)	(0.025)	(0.032)	(0.024)	(0.020)	(0.026)
Log(Brand Products)	0.015	0.008**	-0.027***	-0.019***	0.046***	0.061***
	(0.016)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Brand Perception	0.100***	0.096***	-0.018**	0.091***	0.144***	0.183***
	(0.028)	(0.006)	(0.007)	(0.006)	(0.005)	(0.007)
Log(1 + Reviews at Purchase)	0.404***	0.462***	0.430***	0.422***	0.361***	0.374***
	(0.021)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)
Log(1 + (Posted - Sold))	-0.599***	-0.645***	-0.595***	-0.617***	-0.568***	-0.578***
	(0.016)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)
Log(1 + Number of Likes)	0.133***	0.123***	0.170***	0.138***	0.053***	0.155***
	(0.023)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
Years	2023	2023	2023	2023	2023	2023
Fixed-effects						
Category	✓	✓	✓	✓	✓	✓
Fit statistics						
Standard-Errors	Category			IID		
Observations	960,443	198,348	118,308	197,330	285,357	161,100
Squared Correlation	0.197	0.217	0.198	0.189	0.192	0.182
Pseudo R^2	0.155	0.173	0.155	0.150	0.150	0.145
BIC	1,126,261.7	227,342.1	136,334.8	232,390.9	336,799.4	190,001.4

This table presents regression results analyzing regresson on sales using a logit model over the whole sample and 5 categories with a total of: 960,443 observations The table present the variable 'Price quintile' as an ordinal categorical variable with reference the first quintile (lowest prices). Quintiles are calculated on category and monthly basis . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4. Logist Regresssion Sold (0/1)

Dependent Variable:	Sold Outcome (0/1)					
Category	Full sample	Sweaters	Tops	Pants	Dresses	Jackets
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Real Person	0.039	-0.124***	-0.023	-0.137***	0.352***	0.006
	(0.111)	(0.013)	(0.017)	(0.013)	(0.011)	(0.015)
Professional Model	0.230	0.050***	0.079***	0.002	0.585***	0.185***
	(0.142)	(0.018)	(0.020)	(0.013)	(0.012)	(0.019)
Catalogue Image	0.212***	0.122***	0.365***	-0.043**	0.352***	0.234***
	(0.076)	(0.020)	(0.026)	(0.022)	(0.019)	(0.020)
Price Quintile: 2	0.060***	0.090***	0.021	0.015	0.035***	0.107***
	(0.021)	(0.016)	(0.019)	(0.015)	(0.012)	(0.017)
Price Quintile: 3	0.199***	0.245***	0.137***	0.178***	0.158***	0.213***
	(0.021)	(0.015)	(0.023)	(0.017)	(0.014)	(0.017)
Price Quintile: 4	0.345***	0.426***	0.269***	0.315***	0.254***	0.399***
	(0.040)	(0.016)	(0.025)	(0.017)	(0.014)	(0.019)
Price Quintile: 5	0.523***	0.628***	0.651***	0.371***	0.426***	0.535***
	(0.058)	(0.018)	(0.023)	(0.018)	(0.015)	(0.021)
Condition Disclosed	-0.175**	-0.103	0.159	-0.309***	-0.119	-0.433***
	(0.077)	(0.097)	(0.160)	(0.118)	(0.103)	(0.130)
Beauty	-0.0010***	-0.0008**	-0.001**	-0.0006	-0.001***	-0.002***
	(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.0003)	(0.0004)
Person in Profile Picture	0.103***	0.104***	0.106***	0.094***	0.108***	0.136***
	(0.007)	(0.024)	(0.032)	(0.024)	(0.020)	(0.026)
Number of Images	0.049***	0.070***	0.042***	0.052***	0.039***	0.055***
	(0.006)	(0.005)	(0.007)	(0.005)	(0.004)	(0.005)
Log(1 + Reviews at Purchase)	0.399***	0.457***	0.424***	0.417***	0.357***	0.368***
	(0.021)	(0.005)	(0.006)	(0.005)	(0.004)	(0.005)
Log(1 + (Posted - Sold))	-0.600***	-0.648***	-0.596***	-0.617***	-0.569***	-0.579***
	(0.016)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)
Log(1 + Number of Likes)	0.134***	0.124***	0.171***	0.139***	0.055***	0.156***
	(0.023)	(0.006)	(0.007)	(0.006)	(0.005)	(0.006)
Brand	✓	✓	✓	✓	✓	✓
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
Years	2023	2023	2023	2023	2023	2023
Fixed-effects						
Category	✓	✓	✓	✓	✓	✓
Fit statistics						
Standard-Errors	Category			IID		
Observations	972,720	200,366	119,600	198,955	290,135	163,664
Squared Correlation	0.197	0.217	0.198	0.189	0.191	0.183
Pseudo R^2	0.155	0.173	0.155	0.150	0.150	0.145
BIC	1,140,983.9	229,557.8	137,936.5	234,427.5	342,487.5	193,129.8

This table presents regression results analyzing regresson on sales using a logit model over the whole sample and 5 categories with a total of: 972,720 observations The table present the variable 'Price quintile' as a categorical variable with reference the first quintile (lowest prices). Quintiles are calculated on category and monthly basis . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5. Logist Regresssion Sold (0/1) - Beauty Picture Interaction - 2023

Dependent Variable:	Sold Outcome (0/1)					
Category	Full sample	Sweaters	Tops	Pants	Dresses	Jackets
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Real Person	-0.019	-0.194***	-0.074**	-0.173***	0.297***	-0.077**
	(0.117)	(0.027)	(0.036)	(0.027)	(0.023)	(0.030)
Catalog Image	0.137	0.040	0.398***	-0.175***	0.350***	0.089**
	(0.105)	(0.038)	(0.051)	(0.041)	(0.040)	(0.040)
Professional Model	0.184	-0.065*	0.090**	-0.016	0.554***	0.096**
	(0.148)	(0.036)	(0.043)	(0.026)	(0.024)	(0.039)
Beauty Category × Real Person	0.001***	0.002***	0.001	0.0008	0.001***	0.002***
	(0.0002)	(0.0005)	(0.0007)	(0.0005)	(0.0004)	(0.0006)
Beauty Category × Catalog Image	0.001**	0.002**	-0.0009	0.003***	-4.82×10^{-5}	0.003***
	(0.0007)	(0.0007)	(0.0010)	(0.0008)	(0.0008)	(0.0008)
Beauty Category × Professional Model	0.001***	0.003***	-7.53×10^{-5}	0.0003	0.0008*	0.002***
	(0.0004)	(0.0007)	(0.0008)	(0.0005)	(0.0005)	(0.0007)
Beauty Category	-0.002***	-0.002***	-0.001**	-0.001**	-0.002***	-0.003***
	(0.0004)	(0.0004)	(0.0006)	(0.0004)	(0.0004)	(0.0005)
Person in Profile Picture	0.113***	0.121***	0.103***	0.099***	0.118***	0.152***
	(0.008)	(0.024)	(0.032)	(0.024)	(0.020)	(0.026)
Brand	✓	✓	✓	✓	✓	✓
Condition	✓	✓	✓	✓	✓	✓
Caption	✓	✓	✓	✓	✓	✓
Color	✓	✓	✓	✓	✓	✓
Material	✓	✓	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓	✓	✓
Price	✓	✓	✓	✓	✓	✓
Reviews	✓	✓	✓	✓	✓	✓
Size	✓	✓	✓	✓	✓	✓
Fixed-effects						
Category	✓	✓	✓	✓	✓	✓
Fit statistics						
Years	2023	2023	2023	2023	2023	2023
Standard-Errors	Category			IID		
Observations	972,720	200,366	119,600	198,955	290,135	163,664
Squared Correlation	0.196	0.216	0.197	0.189	0.191	0.182
Pseudo R^2	0.154	0.173	0.155	0.149	0.149	0.144
BIC	1,141,441.5	229,743.0	137,998.2	234,545.2	342,592.7	193,230.1

This table presents logistic regression results analyzing the relationship between image categories and the likelihood of a product being sold across the full sample and five subcategories (Sweaters, Tops, Pants, Dresses, and Jackets), using a total of 972,720 observations. Interaction terms with the Beauty Category variable (constructed by dividing the beauty score into deciles) capture how the attractiveness of images influences sales likelihood differently for each image type. Fixed effects are applied at the category level, and controls include brand, product condition, caption length, color, material, month of posting, price, reviews, and size. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7.2 Beauty

Table A.6. Logistic Regression on Picture Type choice for Sweaters

Dependent Variables:	Homemade Image	Real Person	Catalog Image	Professional Model
Category	Sweaters			
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.661***	0.006	0.758***	0.868***
	(0.013)	(0.014)	(0.022)	(0.019)
Condition Disclosed	0.084	0.016	-0.204	-0.055
	(0.105)	(0.115)	(0.163)	(0.149)
Log(1 + Reviews at Posting)	-0.195***	0.102***	0.137***	0.176***
	(0.006)	(0.007)	(0.010)	(0.009)
Log(1 + (Posted - Sold))	-0.023***	0.111***	-0.061***	-0.095***
	(0.005)	(0.006)	(0.009)	(0.007)
Log(Posted)	0.106***	-0.100***	-0.146***	0.031**
	(0.007)	(0.008)	(0.011)	(0.010)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors	IID			
Observations	161,914	161,914	161,914	161,914
Squared Correlation	0.094	0.045	0.032	0.045
Pseudo R^2	0.071	0.041	0.053	0.061
BIC	207,571.9	175,240.5	87,174.7	109,340.2

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalog Image, and Professional Model. The regression analyzes in detail the Sweaters. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A.7. Logistic Regression on Picture Type choice for Tops

Dependent Variables:	Homemade Image	Real Person	Catalog Image	Professional Model
Category		Tops		
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.908***	0.366***	0.370***	0.895***
	(0.017)	(0.018)	(0.030)	(0.023)
Condition Disclosed	0.211	-0.187	0.458	-0.210
	(0.179)	(0.175)	(0.390)	(0.207)
Log(1 + Reviews at Posting)	-0.217***	0.135***	0.150***	0.112***
	(0.007)	(0.008)	(0.014)	(0.010)
Log(1 + (Posted - Sold))	0.023***	0.068***	-0.110***	-0.084***
	(0.007)	(0.007)	(0.012)	(0.009)
Log(Posted)	0.066***	-0.034***	-0.185***	0.024**
	(0.009)	(0.010)	(0.015)	(0.012)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors		IID		
Observations	98,643	98,643	98,643	98,643
Squared Correlation	0.116	0.066	0.018	0.043
Pseudo R^2	0.087	0.056	0.030	0.049
BIC	125,642.3	113,516.7	49,137.5	80,596.4

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalog Image, and Professional Model. The regression analyzes in detail the Tops. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8. Logistic Regression on Picture Type choice for Pants

Dependent Variables:	Homemade Image	Real Person	Catalog Image	Professional Model
Category		Pants		
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-0.635***	-0.023	0.451***	0.727***
	(0.013)	(0.015)	(0.026)	(0.015)
Condition Disclosed	0.277**	-0.045	0.120	-0.287**
	(0.128)	(0.131)	(0.239)	(0.128)
Log(1 + Reviews at Posting)	-0.222***	0.124***	0.084***	0.140***
	(0.006)	(0.007)	(0.012)	(0.007)
Log(1 + (Posted - Sold))	0.013**	0.087***	-0.018	-0.097***
	(0.005)	(0.006)	(0.011)	(0.006)
Log(Posted)	0.111***	-0.078***	-0.120***	-0.029***
	(0.007)	(0.008)	(0.013)	(0.008)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors		IID		
Observations	157,514	157,514	157,514	157,514
Squared Correlation	0.103	0.051	0.012	0.052
Pseudo R^2	0.078	0.046	0.025	0.050
BIC	200,789.1	169,009.7	71,231.5	166,905.8

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalog Image, and Professional Model. The regression analyzes in detail the Pants. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.9. Logistic Regression on Picture Type choice for Dresses

Dependent Variables:	Homemade Image	Real Person	Catalog Image	Professional Model
Category		Dresses		
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-1.34***	0.428***	0.532***	1.15***
	(0.011)	(0.012)	(0.024)	(0.013)
Condition Disclosed	0.152	-0.118	-0.134	0.0007
	(0.118)	(0.118)	(0.223)	(0.124)
Log(1 + Reviews at Posting)	-0.160***	0.059***	0.058***	0.138***
	(0.005)	(0.005)	(0.010)	(0.006)
Log(1 + (Posted - Sold))	0.109***	0.027***	-0.074***	-0.141***
	(0.005)	(0.005)	(0.009)	(0.005)
Log(Posted)	-0.043***	0.020**	-0.022*	0.027***
	(0.006)	(0.006)	(0.012)	(0.006)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors		IID		
Observations	239,264	239,264	239,264	239,264
Squared Correlation	0.157	0.049	0.010	0.083
Pseudo R^2	0.121	0.043	0.025	0.080
BIC	291,506.9	261,852.9	95,031.3	238,013.3

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalog Image, and Professional Model. The regression analyzes in detail the Dresses. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10. Logistic Regression on Picture Type choice for Jackets

Dependent Variables:	Homemade Image	Real Person	Catalog Image	Professional Model
Category		Jackets		
Model:	(1)	(2)	(3)	(4)
Price Quintile: Linear	-1.23***	0.267***	1.14***	1.29***
	(0.015)	(0.017)	(0.026)	(0.024)
Condition Disclosed	0.084	0.120	-0.022	-0.315*
	(0.137)	(0.152)	(0.203)	(0.169)
Log(1 + Reviews at Posting)	-0.196***	0.100***	0.104***	0.172***
	(0.006)	(0.007)	(0.010)	(0.010)
Log(1 + (Posted - Sold))	-0.004	0.082***	-0.060***	-0.075***
	(0.006)	(0.007)	(0.009)	(0.008)
Log(Posted)	0.058***	-0.041***	-0.084***	0.013
	(0.008)	(0.008)	(0.011)	(0.011)
Brand	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Size	✓	✓	✓	✓
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Convergence	TRUE	TRUE	FALSE	TRUE
Standard-Errors		IID		
Observations	131,712	131,712	131,712	131,712
Squared Correlation	0.140	0.031	0.047	0.063
Pseudo R^2	0.106	0.028	0.070	0.085
BIC	163,174.7	139,233.5	80,949.9	91,322.3

This table presents logistic regression results analyzing the determinants of image type choice in product listings on a second-hand marketplace. The dependent variables represent different image categories: Homemade Image, Real Person, Catalog Image, and Professional Model. The regression analyzes in detail the Jackets. Controls for brand, caption length, color, material, month of posting, and size are included. Fixed effects are applied at the category level. Standard errors are clustered by category. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.11. Logist Regresssion Sold (0/1) - Beauty Picture Interaction Category

Dependent Variable:	Sold Outcome (0/1)			
Model:	(1)	(2)	(3)	(4)
Real Person	0.169	-0.395*	-0.007	0.053
	(0.124)	(0.235)	(0.122)	(0.109)
Catalogue Image	0.368***	-0.136	0.190***	0.155
	(0.086)	(0.201)	(0.073)	(0.109)
Professional Model	0.339***	0.191*	0.242	0.183
	(0.098)	(0.113)	(0.150)	(0.146)
Distance from Average Beauty × Real Person	0.010**	0.014**	0.005***	
	(0.005)	(0.006)	(0.001)	
Distance from Average Beauty × Catalogue Image	0.010***	0.012**	0.003**	
	(0.004)	(0.005)	(0.001)	
Distance from Average Beauty × Professional Model	0.005	0.0010	0.0007	
	(0.005)	(0.005)	(0.001)	
Distance from Average Beauty	-0.006***	-0.002	-0.003***	
	(0.001)	(0.004)	(0.0005)	
Brand	✓	✓	✓	✓
Condition	✓	✓	✓	✓
Caption	✓	✓	✓	✓
Color	✓	✓	✓	✓
Material	✓	✓	✓	✓
Month of Posting	✓	✓	✓	✓
Price	✓	✓	✓	✓
Reviews	✓	✓	✓	✓
Size	✓	✓	✓	✓
Beauty Sample	Bottom	Top	The middle	No Profile Picture
Year	2023	2023	2023	2023
Fixed-effects				
Category	✓	✓	✓	✓
Fit statistics				
Standard-Errors	Category			
Observations	100,000	100,000	602,610	170,110
Squared Correlation	0.205	0.183	0.194	0.204
Pseudo R^2	0.163	0.142	0.153	0.160
BIC	116,387.4	119,898.2	708,441.0	198,686.1

This table presents regression results analyzing regresson on sales using a logit model over the whole sample and 5 categories with a total of: 602,610 observations . * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables Description

- Sale Outcome$_{i,j}$ is a binary variable indicating whether the product i was sold (1) or remained unsold (0).
- Picture Category$_i$: A set of variables indicating the category of the image, distinguishing whether the first picture of the product is a homemade photo taken in a domestic setting, an image featuring the seller's body, a professional catalogue image, or one showcasing professional models.
- Ad Characteristics$_i$: A set of variables representing features of the advertisement:
  - **Price Quintile**: A categorical variable representing the relative price of the product within its category and posting month, divided into quintiles.
  - **Caption Length Category**: A categorical variable indicating whether the listing has no caption, a short caption, or a long caption.
  - **Posting Month**: A control for temporal variations in posting, capturing seasonal trends or other time-related factors.
  - **Condition Disclosure**: A binary variable indicating whether the condition of the product is explicitly disclosed.
- Reputation and Experience$_{j,t}$: Variables reflecting the seller's reputation and activity level:
  - **Log(1 + Reviews at Posting)**: The logarithm of one plus the number of reviews the seller had received at the time of posting, reflecting their historical reputation.
  - **Log(1 + Posted-Sold Difference)**: The logarithm of one plus the difference between products posted and sold by the seller, reflecting unsold inventory.
  - **Log(Cumulative Posted)**: The logarithm of the total number of items the seller has listed to date, capturing their experience level.
- Brand Characteristics$_i$: Variables reflecting the prominence and perception of the brand:
  - **Log(Brand Product Count)**: The logarithm of the total number of products listed under the same brand, indicating the popularity or prevalence of the brand.
  - **Brand Perception**: A variable capturing the perceived reputation of the brand.
- Product Characteristics$_i$: Variables describing specific attributes of the product:
  - **Size Grouped**: A categorical variable for product size, with reference group "XS."

- **Primary Color**: A categorical variable for the dominant color of the product, with reference "no_color."
- **First Material**: A categorical variable for the primary material of the product, with reference "no_material."

IQA

- BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator): This metric evaluates image quality without requiring a reference image, focusing on natural scene statistics to quantify distortions. A lower BRISQUE score indicates higher image quality, making it suitable for analyzing real-world images with unknown degradations.
- NIQE (Naturalness Image Quality Evaluator): Similar to BRISQUE, NIQE is a no-reference image quality metric that measures deviations from natural image statistics. It provides a score that reflects how close an image is to the statistical properties of high-quality images, with lower scores representing better quality.
- MUSIQ (Multi-Scale Image Quality): This metric evaluates image quality by considering multiple scales and assessing both the global and local features of an image. It is particularly effective for images with complex textures and varying levels of detail.
- DBCNN (Deep Bilinear Convolutional Neural Network): This deep learning-based metric assesses image quality using a bilinear architecture, combining local and global information to predict perceived quality scores. It leverages pre-trained neural networks for robust evaluations.
- PAQ (Perceptual Aesthetics Quality): This metric measures the perceptual aesthetic quality of images, focusing on elements such as composition, lighting, and visual appeal. It is particularly relevant for understanding consumer-facing aspects of product images.
- PIQE (Perception-based Image Quality Evaluator): PIQE is another no-reference metric that quantifies image quality by identifying and analyzing distortions such as noise, blur, and compression artifacts. Lower PIQE scores correspond to higher quality images.
- IL-NIQE (Integrated Local Naturalness Image Quality Evaluator): IL-NIQE extends the NIQE methodology by incorporating local image features and naturalness statistics. This metric provides a more granular assessment of image quality, especially for images with diverse textures and content.

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