Proceedings of the Seventeenth International AAAI Conference on Web and Social Media (ICWSM 2023)

Characterizing and Identifying Socially Shared Self-Descriptions in Product Reviews

Lu Sun[1], F. Maxwell Harper[2], Chia-Jung Lee[2], Vanessa Murdock[2] and Barbara Poblete[2,3]
[1] University of California San Diego, USA
[2] Amazon.com, USA
[3] Department of Computer Science, University of Chile, Chile
l5sun@ucsd.edu, maxharp3r@gmail.com, cjlee@amazon.com, vmurdock@amazon.com, bpoblete@dcc.uchile.cl

Abstract

Online e-commerce product reviews can be highly influential in a customer's decision-making processes. Reviews often describe personal experiences with a product and provide candid opinions about a product's pros and cons. In some cases, reviewers choose to share information about themselves, just as they might do in social platforms. These descriptions are a valuable source of information about who finds a product most helpful. Customers benefit from key insights about a product from people with their same interests and sellers might use the information to better serve their customers needs. In this work, we present a comprehensive look into voluntary self-descriptive information found in public customer reviews. We analyzed what people share about themselves and how this contributes to their product opinions. We developed a taxonomy of types of self-descriptions, and a machine-learned classification model of reviews according to this taxonomy. We present new quantitative findings, and a thematic study of the perceived purpose descriptions in reviews.

1 Introduction

Online customer product reviews are an important source of information for customers making a purchase decision (Floyd et al. 2014), and they have been shown to directly influence product sales (Chevalier and Mayzlin 2006; Resnick and Zeckhauser 2002). Some reviewers include descriptive information about themselves in their reviews, and this information helps readers assess whether a product is suitable for them. Intuitively, self-descriptions contextualize and personalize product reviews by sharing details that allow readers to connect a product with a person. People relate to opinions by other people like them (McPherson, Smith-Lovin, and Cook 2001), and their perception of who uses the product may be shaped by the self-description of the reviewer (Kressman et al. 2006; Japutra, Ekinci, and Simkin 2019). For example, a product review that states *"I am a non-traditional student, and this bag is great for both work and school"* suggests the suitability of the product for work or school, but also suggests the age and education of the reviewer, which some customers may find relatable.

While this information is potentially useful, much of the literature on self-description in e-commerce is centered on information provided to the e-commerce service as part of the customer transactions or from standalone reviewer profiles (Joinson et al. 2010). To the best of our knowledge, there is no prior work characterizing self-description in e-commerce reviews to understand how and what people choose to publicly share about themselves. To address this, we propose the following research questions:

- ***RQ$_1$: What kinds of self-descriptions can be found in reviews?*** (Are they the same for all products? How frequently do people self describe?)
- ***RQ$_2$: Can self-descriptions in reviews be automatically identified and analyzed at a larger scale?*** (Are they a valuable source of product information?)
- ***RQ$_3$: How are self-descriptions used in reviews?*** (Do they serve different purposes? How do they help the reviewer convey their opinion?)

We propose a systematic, mixed method study on Amazon.com reviews. We used an iterative, inductive approach to map self-descriptions into a comprehensive taxonomy, and developed models to categorize self-descriptions according to the taxonomy. Finally, we provide a qualitative and quantitative analysis of self-description in reviews to characterize the use of self-descriptions.

We found that approximately 13% of reviews contain self-descriptive information, shared in a variety of ways. We identified 12 distinct types of personally descriptive information, which are distributed differently among different types of products. For example, people share more about their physical appearance when reviewing beauty products and apparel; they share more about their personal background and experience when reviewing books; and, unsurprisingly, people disclose medical information when reviewing health care products.

We classified reviews as containing self-description (or not) with 94% precision, and further classified examples of self-description as one of 12 types with a precision of between 57% (for hobbies) and 94% (for appearance). Based on this result, we performed quantitative analysis of a large sample of reviews, and observed that nearly all categories of self description are predictive of helpfulness votes. Further, reviews with high star-ratings contained more self-descriptions than those with low ratings. This is consistent with the findings of our thematic analysis, which reveals that reviewers often share personal details that lend evidence of product quality, or provide context for the use of a product.

The main contributions of the work are a comprehensive taxonomy of types of self-descriptions used in e-commerce reviews (Section 3), a RoBERTa-based method to automatically identify and label types of self-descriptions (Section 5), a quantitative analysis of self-descriptive data (Section 6), and a thematic analysis of the perceived purpose of self-description in reviews (Section 7).

The rest of the paper is organized as follows: Section 2 presents related work that provides the context for the current research. Section 3 presents a self-description taxonomy for reviews. Sections 4 and 5 describe the data and labeling process, as well as the classification models for self-descriptions. Sections 6 and 7 present a quantitative analysis and a thematic study. The paper ends with a discussion of the results (Section 8) and conclusions (Section 9).

2 Related Work

Self-disclosure has been defined as *"the process of making the self known to others"*, often carried out by sharing one's thoughts, opinions, tastes and experiences (Jourard and Lasakow 1958; Joinson and Paine 2007). It is a communicative act that can help people develop close relationships and maintain trust through sharing of personal information (Altman and Taylor 1973; Ren, Kraut, and Kiesler 2007; Bruss and Hill 2010). However, we restrict the scope of our current study to a subset of self-disclosure that pertains to sharing of information that describes oneself as an individual (Forman, Ghose, and Wiesenfeld 2008).

Self-disclosure in online social platforms. Self-disclosure can play an important role in forming and maintaining social relationships (Barak and Gluck-Ofri 2007; Bazarova 2012; Bak, Kim, and Oh 2012; Jiang, Bazarova, and Hancock 2013; Bazarova and Choi 2014; Ma, Hancock, and Naaman 2016; Wang, Burke, and Kraut 2016; Saha et al. 2021). On social media, people share personal life events and important life changes in order to gain social support. Previous studies also found that more self-disclosure is associated with intimacy among friends and more positive interpersonal impressions (Sprecher, Treger, and Wondra 2013; Park, Jin, and Jin 2011; Bak, Kim, and Oh 2012). In online mental health forums, self-disclosures have been observed to produce benefits from a clinical perspective (Smyth 1998; Pennebaker and Chung 2007; Suler 2004; Balani and De Choudhury 2015).

Previous research found that high self-disclosure social media posts receive fewer upvotes, but more comments and a higher response rate (Balani and De Choudhury 2015; Valizadeh et al. 2021). Researchers observed a negative association between self-disclosure and network size on Twitter (Wang, Burke, and Kraut 2016).

Online social network user profiles are a common way in which users self-disclose personal information. The goal of this is usually self-broadcasting, or to attract interest (Kim et al. 2016; Gibbs, Ellison, and Lai 2011; Uski and Lampinen 2016). Profiles can influence perceptions of trustworthiness, as they allow users to assess communicators (Berger and Calabrese 1974; Donath 2007; Spence 2002; Ma et al. 2017). Social media user profiles, along with purchase intent declared publicly in social media platforms has been studied as a source for product recommendation (Zhao et al. 2014, 2016). Mostly by relating user demographics extracted from the profile with products that users claim in social media that they want to buy.

Our work differs from social media studies in that we investigate distinctive self-descriptive patterns that exist in e-commerce reviews. We study review content and not profiles, in relation to product types and work toward understanding self-descriptive information and its usefulness in this context.

Self-disclosure in e-commerce. Self-disclosures in product reviews can serve as an important cue to shape readers' opinions about products and the trustworthiness of reviews themselves (Forman, Ghose, and Wiesenfeld 2008). Displaying information about the reviewer's profile next to their review (including real name, location, nickname, and hobbies) increases positive attitudes toward the review (**?**Ghose and Ipeirotis 2010). Showing the reviewer's name and location is correlated with more helpful votes and being perceived as more helpful by peers (Forman, Ghose, and Wiesenfeld 2008). The prevalence of reviewers' descriptions of identity has been associated with increases in subsequent online product sales (Forman, Ghose, and Wiesenfeld 2008). In a study of host profiles on Airbnb, having a variety of self-disclosure categories (including work, education, origin, and hospitality) positively influenced hosts' perceived trustworthiness (Ma et al. 2017).

In relation to self-disclosure in review text, Shin et al. (2017) study the influence on perceived review persuasiveness. They ran a small comparative user study and showed two types of Yelp[1] reviews: one with high self-disclosure and another with low self-disclosure and found that there is no significant effect on perceived persuasiveness. On the contrary, Hamby, Daniloski, and Brinberg (2015) compared two types of user-generated reviews: one that presented a story of the reviewer's experience with the product, and another that only presented a list of the product features. They found that reviews describing personal experiences led readers to be more engaged, which in turn increased positive attitudes toward the review's message. Hence, there is still no consensus about the extent to which self-disclosures influence the utility of reviews.

Our current research complements existing work in several ways. We study in depth and for the first time the different types of self-descriptive disclosure in e-commerce review content. We also investigate the perceived purpose of this descriptive information in relation to reviewer opinions. In addition, we automate the process of identifying and categorizing types of self-descriptive information in reviews. This allows us to conduct the first quantitative study on a large sample of reviews and report our findings.

[1]https://yelp.com, visited March 2023.

3 A Taxonomy of Self-Description

In this section we detail a proposed taxonomy of self descriptions in e-commerce reviews, shown in Table 1. For this purpose, we used the publicly available Amazon.com reviews dataset.[2] We selected reviews from the most recent full year available (2014), and randomly sampled 825,000 reviews from the top 20 product categories with the most reviews. We refer to this sample as the *review dataset*.

Manual taxonomy creation. In order to identify the kinds of self-descriptions used in reviews, we manually inspected 150 reviews from each product category. We labeled these reviews based on broad categories derived from different types of self-disclosure described in prior work. These categories consisted mostly of self disclosure in areas other than e-commerce, such as *search* (Weber and Jaimes 2011; Bi et al. 2013), *online profiles (in e-commerce and social media)* (Ma, Hancock, and Naaman 2016; Ma et al. 2017), *social media platforms* (Bak, Kim, and Oh 2012; Wang, Burke, and Kraut 2016; Zhao et al. 2016; Walton and Rice 2013; Saha et al. 2021; Zhao et al. 2014, 2016) and *online communities* (Kou and Gray 2018; Valizadeh et al. 2021; Balani and De Choudhury 2015; Yang, Yao, and Kraut 2017; Barak and Gluck-Ofri 2007; Yang, Yao, and Kraut 2017).

We found self descriptions varied depending on the product category. For example, reviewers tended to volunteer information about their own health conditions when reviewing vitamin supplements. They talked more about their physical appearance when reviewing clothing. They described relationships when buying gifts for others. In addition, we observed that reviews containing mentions of first-person pronouns had a higher likelihood of self-description ($\approx 21\%$).

Using an inductive analysis approach (Hsieh and Shannon 2005), we refined the resulting categories. Two researchers independently coded an additional 300 reviews (randomly sampled from those that contained first-person pronouns) and then worked together to add, combine, or eliminate categories iteratively. For example, similar self descriptions like "body measure" and "physical appearance" were merged into the category "appearance". The category "other" was introduced to capture less frequent types of self-description such as statements of political affiliation (see Table 1).

Crowdsourced validation. We validated the resulting taxonomy by conducting a crowdsourced study on a set of approximately 1000 reviews. Given the scarcity of self descriptions in relation to the complete set of reviews, for this evaluation we pre-filtered reviews to increase the likelihood they contain self descriptions. This pre-filtering was done using a preliminary self-description classifier, which we created for this purpose ("SD-detect" described in Section 5). Each crowd worker was asked to label reviews according to the proposed taxonomy described in Table 1. From the set of 1000 pre-filtered reviews, only 83 reviews ($\approx$8%) were labeled as without self description (i.e., false positives of the preliminary classifier), and six were labeled as "other".

[2]https://s3.amazonaws.com/amazon-reviews-pds/readme.html visited September 2022

4 Types of Self-Description in Reviews

We seek to understand general aspects of self-description in reviews, and create a classification model for self-descriptions. To this end, we set up a new crowdsourcing task to label reviews. Using the crowdsourcing platform Appen[3,4], we asked workers to judge whether a review contained self-description (*SD* for short) via a simple yes or no question. If yes, they were asked to select the categories from the taxonomy they thought the review belonged to. We provided definitions and examples of each category. Two raters annotated each review, and if the two did not agree, a third rater was a tie-breaker. We controlled the quality of the annotations by including gold-standard tasks (Downs et al. 2010), which consisted of a manually labeled subset of reviews, annotated by two of our own researchers. We discarded annotations from workers who had less than 90% accuracy on the gold standard questions.

As a result of this process, 254 (12.7%), out of 2,000 randomly-sampled reviews, were labeled by crowd workers as containing self descriptions, with an overall Cohen's Kappa of 0.81. Table 2 shows a detailed breakdown of self-description frequency types and inter-rater reliability (IRR). Most categories achieved good to excellent agreement scores (IRR greater than 0.60) (Cicchetti 1994), with the exception of "personal hobbies" that had the highest discrepancy among raters (IRR of 0.42).

Reviews labeled by crowd workers covered a wide range of different product types. We expected differences in the use of self-descriptions depending on the type of product. In answer to RQ_1 (*What kinds of self-description can be found in reviews?*), Figure 1 shows the distribution self descriptions across product types. We observe that people tend to self-describe the most when reviewing products related to "Apparel","Books", "Pet Products" and "Toys".

Figure 2 shows the detailed distribution of SD categories across product types. Here, we see that users frequently mention location when reviewing "Automotive" products (e.g., *"I was up in the Sierras and the temperature was around 5 degrees, the battery was dead"*). Unsurprisingly, people tend more to mention their appearance when reviewing beauty products (e.g., *"I have brown curly hair"*), and to discuss their medical conditions when reviewing health care products (e.g., *"I'm an active 71 year old man with persistent knee and back pain"*). In addition, Figure 2 shows that "relationship status" is the most frequent self-description category for many product types, accounting for 60.2% of the self-descriptive reviews in our sample. "Relationship status" includes descriptions of who the product was purchased for (such as *"ordered this for my sister"* or *"my 3-year-old daughter's birthday gift"*), which explains why it is so prevalent in the data. Next to this, the most common self-description categories observed were "appearance" (8.3%) and "medical" (6.4%).

[3]https://appen.com/ visited April 2023.

[4]We paid $0.19 for rating each review based on an estimated rate of $15/hr. The average annotation time per review was 40 seconds.

Category	Description	Example
Age	age, e.g., years, seniority, or status	*"As a woman in my mid 50s, this is not for me."*
Appearance	appearance, e.g., weight, height, hair style	*"I'm 5'6 with shoulder length curly hair."*
Education	educational qualifications or status, e.g., school, major, class	*"I'm a college student."*
Ethnicity/Race	racial or cultural identity	*"I am Asian, this product works pretty well for me."*
Gender/Sexual orientation	gender identity or sexual orientation	*"I am gay, and not religious."*
Location	past or present location, e.g., city, country	*"I live in Alaska."*
Medical	health condition, mental health condition, symptoms, experience, diagnosis, or treatment	*"My disorder is hard to describe and I'm often misunderstood."*
Occupation	current or past job or professional experience	*"This would be an appropriate book for my clients, I'm a psychologist."*
Hobbies	activities and interests, e.g., favorite books, music, characters	*"Big fan of [author] since I was a kid and love sense of history."*
Relationship status	family members, marital status	*"My wife and daughters were watching [show] with me and it was funny!"*
Religion	religious affiliation or beliefs	*"As a dedicated Christian, initially I didn't want to read it."*
Other	personal experience	*"I experienced abusive behavior when I was young."*
	political affiliation	*"This pin is perfect for showing that I'm a democrat."*
	income	*"I earn less than minimum wage."*
	name, spoken language	*"My name is [name], and my native language is Spanish."*
	personality, personal traits	*"Great book! I am soft spoken and introverted, and this helped me."*

Table 1: Examples of self-description categories from prior work in e-commerce reviews, along with a description and example

Category	Freq.	IRR
age	3.0%	0.706
appearance	8.3%	0.700
education	0.8%	0.575
ethnicity/race	0.8%	0.796
gender/orientation	3.0%	0.565
location	4.5%	0.846
medical	6.4%	0.696
occupation	4.9%	0.708
personal hobbies	4.2%	0.415
relationship status	60.2%	0.840
religion	1.5%	0.726
others	2.3%	

Table 2: Self-description category relative frequency and inter-rater reliability (IRR) score.

5 Classifying Self-Description

In this section, we address research question RQ_2: *Can self-descriptions in reviews be automatically identified and analyzed at a larger scale?* We treat the question as two distinct machine learning classification tasks: 1) detect whether a review contains self-description ("SD-detect"), and then, for those examples that contain self-description, 2) identify the types of self-descriptions ("SD-category'), as described in the taxonomy in Section 3. The intuition behind this cascade approach is to separate reviews that do not contain informative self descriptions, from those that can be further categorized into the taxonomy.

We observed that reviews that only contain relationship status do not provide other interesting self-descriptive information. Since relationship descriptions account for more than half of the self-descriptions in the data (see Table 2), we formulated the first classification step as a 3-way multi-class classifier that discriminates between the classes "no self-description", "self-description relationship" (i.e., when the review contains *only* self-descriptions of "relationship status") and "self description" (i.e., all other types of self descriptions). While it is more intuitive to frame this first problem as a binary classification (self-description vs. no self-description), in practice we found that a 3-way classifier worked better than a binary classifier trained on the same data. In addition, performance was improved for the second, more specialized multi-label classifier ("SD-category') that categorizes the "self description" output from the first classifier into the taxonomy categories.

Both SD-Detect and SD-Category models used the same configuration. A RoBERTa (Liu et al. 2019) language model extracted feature representations from the first 512 tokens of each review, adding a softmax layer with L2 regularization for classification. We used the CLS token for feature representation, and the Adam optimizer. Text was pre-processed using standard text normalization techniques, such as replacing numbers using underscores, and removing special characters such as quotation marks. Each model was trained for

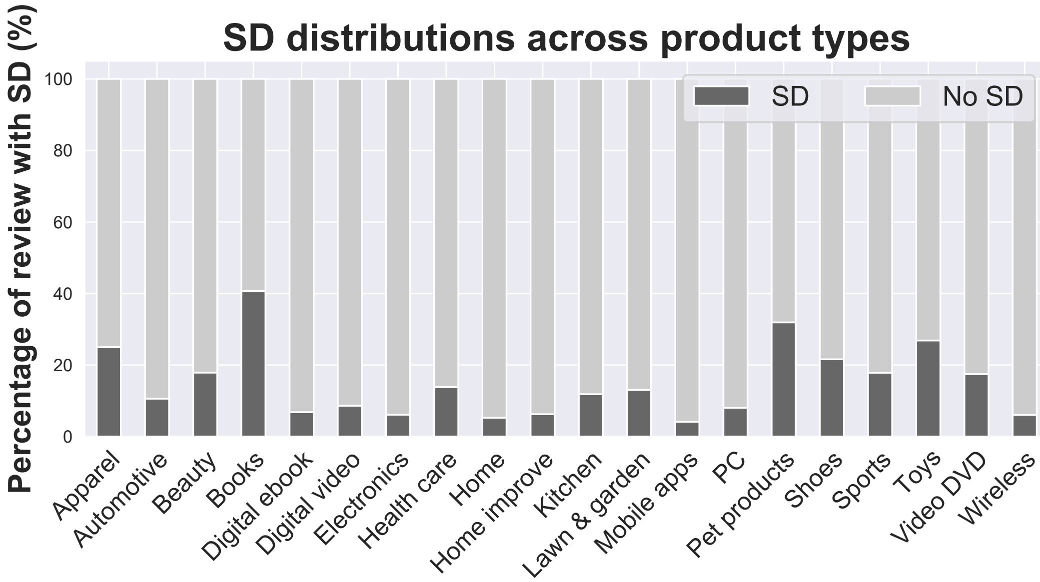

Figure 1: Distribution of self-description in reviews by product type according to the 2000-review crowdsourced annotations.

10 epochs with batch size 16, the learning rate of the Adam optimizer was 5e-5, and the weight decay for L2 regularization was 0.001. We used 10-fold cross validation, minimizing cross entropy loss.

SD-detect was trained on the 2000 labeled examples described in Section 4. This data contains few examples for each specific category of self description other than “relationship status”. To address this imbalance, we used the SD-detect model to identify the top 1000 review candidates classified as “self description” in the unlabeled portion of our dataset. We annotated these candidates using the same crowdsourcing mechanism described in Section 4. This data was used to train the second model.

Table 3 summarizes the performance of the two models, including the number of training instances and predicted positives over the entire review dataset for each class. The SD-detect model achieved an overall micro F1 score of 0.94, with high classification accuracy for the “no self description” class (F1=0.96) and “SD relationship” class (F1=0.85). Performance for the “self description” class (F1=0.61) was lower, likely due to the class imbalance in the data and wide variation among types of self-descriptions found in this class. However, given the low incidence of this class in the dataset we consider this to be a reasonable starting point for automatic identification of fine-grained self description categories that are not “relationship status”. The SD-category model achieved F1 scores ranging from 0.60 to 0.95, with an overall micro F1 score of 0.86, weighted by the number of positive instances. Performance is highest for the “appearance” category (F1=0.95), which has the most training data, and lowest for “personal hobbies” (F1=0.60) and “ethnicity” (F1=0.72) where the number of training instances is much lower. Note that “personal hobbies” also had the lowest agreement among annotators.

class	precision	recall	F1	instances	predicted
no SD	0.97	0.96	0.96	1746	741,485
SD	0.61	0.61	0.61	103	17,000
SD relationship	0.82	0.88	0.85	151	66,530
overall	0.94	0.94	0.94	2000	825,015

(a) SD Detection model performance (averaged across folds)

class	precision	recall	F1	instances	predicted
age	0.75	0.87	0.80	117	2,026
appearance	0.94	0.95	0.95	431	3,004
education	0.81	0.94	0.86	49	359
ethnicity	0.67	0.84	0.72	34	326
gender	0.69	0.91	0.78	107	834
location	0.77	0.94	0.84	45	519
medical condition	0.82	0.88	0.84	115	4,081
occupation	0.78	0.86	0.81	153	1,458
personal hobbies	0.57	0.71	0.60	60	2,353
religion	0.78	0.88	0.82	37	224
overall	0.84	0.90	0.86	1000	17,000

(b) SD Categorization model performance (averaged across folds)

Table 3: Model performance metrics, *overall* indicates micro-average scores, *instances* indicates number of labeled training/testing instances and *predicted* indicates number of predicted instances for the class. Fig.3a shows metrics for the SD detection model and Fig.3b show metrics for the SD categorization model. Note that for this last model more than one category can be predicted for an instance.

6 Quantitative Analysis

In an e-commerce store, customers are often asked to rate the products they buy with a number or “star rating” (which is a number typically between one and five). Star ratings are often paired with a free-form text field to elaborate why the rating was given. Customers can vote on whether they found

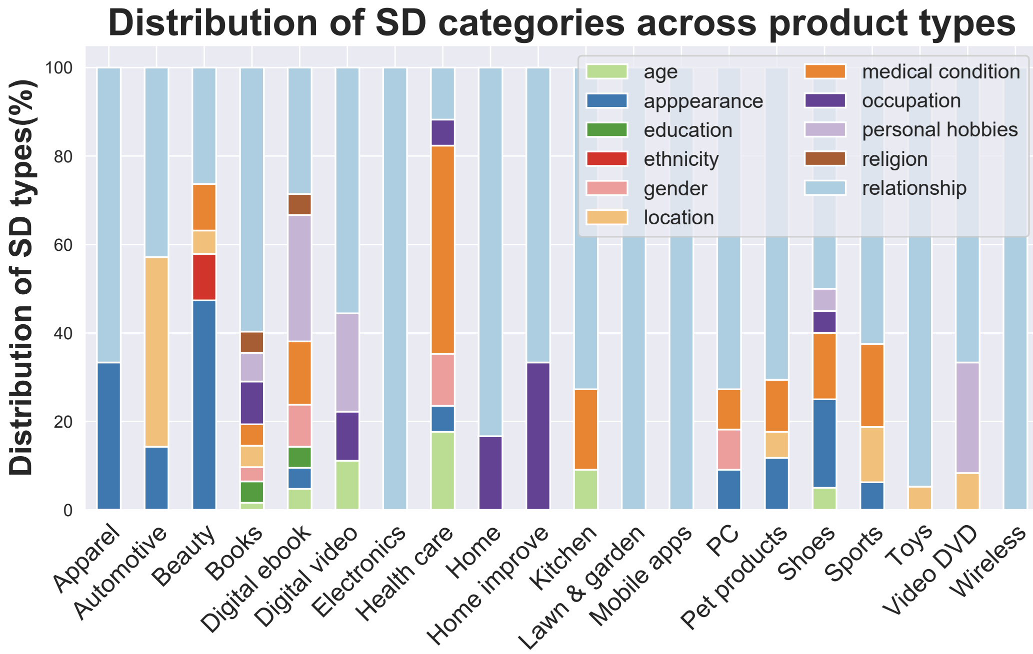

Figure 2: Distribution of self-description category across product types according to the 2000-review crowdsourced annotations.

the review helpful. We hypothesize that a customer might find one review more helpful than another, when the review is more personal, and the reviewer is more relatable. In addition, we hypothesize that the reviewer's willingness to share information about themselves is related to their star rating.

To investigate these hypotheses we conducted a regression analysis on the entire Amazon review dataset (825,000 reviews) described in Section 3. We used the classifiers described in Section 5 to predict the presence of self-descriptions. We obtained the predictions of SD-relationship and SD-category for each review, and subsequently use these predictions as independent variables (i.e. features) to predict the dependent variables (i.e. helpfulness or star ratings). Specifically, three regression models were developed: a baseline model, a binary model and a category model. All independent and dependent variables were standardized before fitting the regressors, such that the resulting coefficients were standardized and the effects are directly comparable.

The baseline model used several simple features as in prior work to predict helpfulness (Gamzu et al. 2021), including the length of the review and the predicted sentiment of the review. We used a sentiment lexicon designed for social media to assign positive and negative sentiment scores to each review as features, following (Hutto and Gilbert 2014). To test the influence of self-description, a second model ("binary") extended the baseline model with an indicator variable describing whether the review contains self-description or not. Specifically, we used the SD-detect classifier described in Section 5, considering predictions of "self description" or "self description relationship" as a "1" while treating "no self description" as "0". To evaluate the influence of the fine-grained categories, a third model ("category") extended the baseline model with indicator variables for each category from the taxonomy. The category features were computed based on the output of both SD classifiers in Section 5, creating an 11-dimensional binary vector with entries corresponding to respective categories for each review.

The results presented in this section are based on the output of automatic classifiers, which may be imperfect. However, this approach allows us to scale our analysis of self-descriptions to a much larger set of reviews. We support the robustness of these findings by repeating the same analysis, with similar results, on a separate set of manually annotated reviews. Details are in the Appendix.

Helpful votes analysis. We conducted a linear regression analysis where the dependent variable reflects the number of helpful votes (i.e., clicks on "this review is helpful") that each review received. The raw helpful votes are available in the original public dataset, with a maximum of 2999, a mean of 0.95, and a standard deviation of 9.36. To make effects comparable in our analysis, we transformed the dependent variable into the logarithm space (with base 10), and standardized all independent and dependent variables. Table 4a summarizes the results of the three fitted linear regression models: baseline, binary, and category described above.

The results suggest that the act of self-description affects how people perceive helpfulness. The category model fits best to the data, improving the baseline and binary model by 3.2% in R-squared. A follow-up ANOVA test on F statistic suggests that the binary model is significantly better than the baseline model with $p < 0.0001$, despite their similarity in R-squared. The same level of significance is observed when comparing the category model to the baseline model. The Bayesian Information Criterion (BIC) score is a method for scoring and selecting a model. We note that the category model demonstrated the lowest BIC score, indicating it is favorable as it has lower model complexity.

The standardized coefficients in the category model indicate that most categories had significant positive effects on the response, with some exceptions such as location and personal hobbies. We conjecture that a reviewer's location (e.g., a city name) may be less helpful to readers located in the different areas (Shin et al. 2017), and hobbies may be highly personal and resonate only with a small number of people who share the hobby. The highest positive coefficients with statistical significance correspond to medical condition (0.0412), appearance (0.0225), and occupation (0.01).

Star rating analysis. We extended the same analysis to the star rating each product received at the time the data was collected. The overall data set leans toward higher star ratings, with a mean of 4.22 and standard deviation of 1.23. We applied standardizing procedures to all the independent and dependent variables.

Similar to the helpfulness analysis, Table 4b shows that the category model best predicts star ratings (i.e. R-squared 0.207), improving the baseline and the binary model by 0.5% and 0.4% respectively. The Anova F statistic shows that the impact brought by incorporating self-description signals is significant, comparing both the binary and the category models respectively to the baseline (both $p < 0.0001$).

On individual predictors, it is expected that the sentiment features are effective in predicting star ratings, resulting in high absolute coefficient values. Beyond those, we note that the binary predictor demonstrates a large positive coefficient (i.e. 0.0677 with $p < 0.0001$). This could be because people often discuss their own contexts and experiences to be more convincing for the high ratings they intend to give. Mentions of medical conditions (0.0323) again top other predictors with higher coefficients. Interestingly, location (0.0061) and personal hobbies (0.0099), while only marginally correlated with helpful votes, demonstrate significantly positive coefficients with respect to star ratings. We note that appearance (-0.0005) and gender (0.0007) were less indicative of star ratings. While we hypothesize that it could be caused by cancelling effects or data sparsity, further analysis is needed, which we leave to future work.

Correlation analysis. In addition to studying how the presence of self description signals could predict helpfulness and ratings, we investigated whether there are patterns to the way people tend to self-describe. Figure 3 illustrates the Pearson's correlation coefficient between each self description category signal. We note that when people reveal gender, they often mention age and appearance as well, as suggested by the higher correlations (i.e. 0.25 and 0.24 respectively). We also found that the pairs of (location, ethnicity) as well as (medical condition, age) demonstrate higher correlation. Personal hobbies appear to correlate with multiple categories such as age, education, location, and occupation, suggesting that hobbies are relevant to broader discussions in reviews.

variable	baseline	SD binary	SD category
Intercept	-7.62e-13	-7.61e-13	-7.61e-13
Length	0.2537*	0.2533*	0.2511*
Positive sentiment	-0.1120*	-0.1104*	-0.1097*
Negative sentiment	0.0173*	0.0187*	0.0172*
Contain SD		0.0224*	
age			0.0137*
appearance			0.0225*
education			0.0037*
ethnicity			0.0028
gender			0.0040*
location			-0.0012
medical condition			0.0412*
occupation			0.0100*
personal hobbies			0.0013
religion			0.0062*
relationship			0.0020
DF	3	4	14
BIC	2.261e+06	2.261e+06	2.259e+06
Adj R-squared	0.092	0.092	0.095
Anova test F-stats		452.088133*	248.764022*

(a) Helpful votes

variable	baseline	SD binary	SD category
Intercept	1.56e-14	1.59e-14	1.58e-14
Length	0.0298*	0.0285*	0.0278*
Positive sentiment	0.2800*	0.2851*	0.2850*
Negative sentiment	-0.2758*	-0.2714*	-0.2720*
Contain SD		0.0677*	
age			0.0084*
appearance			-0.0005
education			0.0079*
ethnicity			0.0010
gender			0.0007
location			0.0061*
medical condition			0.0323*
occupation			0.0131*
personal hobbies			0.0099*
religion			0.0082*
relationship			0.0591*
DF	3	4	14
BIC	2.16e+06	2.15e+06	2.15e+06
Adj R-squared	0.201	0.206	0.207
Anova test F-stats		4723.19416*	483.64034*

(b) Star rating

Table 4: Three standardized regression models predicting review helpfulness (Table 4a) and star-rating (Table 4b) using the Amazon.com dataset described in §3: a baseline model with no self-description features, a model with a binary self-description feature, and a model with per-category self-description features. Including self description categories significantly improved the fit of the regression model. P-value significance code $< .0001^*$

7 Thematic Analysis

To answer RQ_3 (*How are self-descriptions used in reviews?*) in this section we report a *thematic analysis* (Braun and Clarke 2006) as a qualitative method for understanding patterns of behavior in reviews. Because this analysis requires reading and distilling information from the reviews, we worked with a representative subsample of the data. We ran-

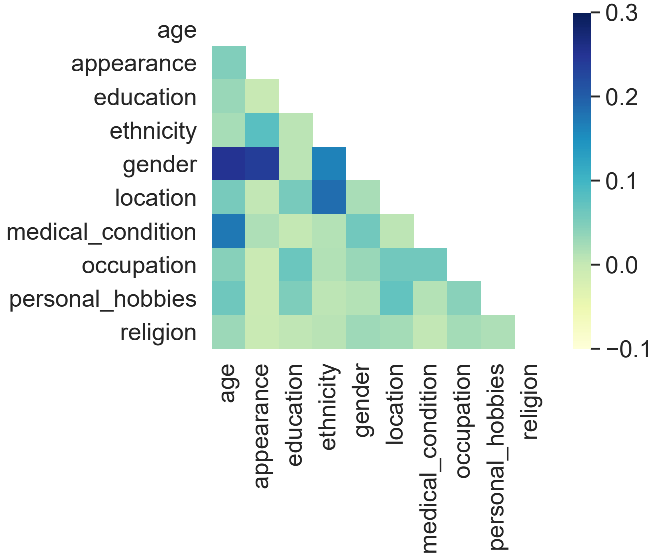

Figure 3: Pearson's correlation coefficient between each self description category signal.

domly sampled 50 reviews from each of the self-description categories predicted by the categorization model described in Section 5. Two researchers independently read through the reviews identifying key phrases, and open coded the reviewers' apparent intention behind the self-description. They discussed and grouped the codes until they arrived at an agreement on the five themes reported below. During this stage, reviews that did not correspond to their predicted category were discarded, not to induce any classifier related errors. Notably, this manual evaluation showed over 90% precision for the predicted reviews in each category (except for "personal hobbies" with 81% precision), indicating good generalization of our automatic classification model.

Theme 1: Self description as context for product use Reviewers often describe themselves to contextualize their personal experience with the product. For example *"Fits really well on me. I am 6'1; and fairly thin. Looks really nice."* describes the fit of a garment for a particular body type. These types of statements implicitly signal that the reviewer is representative of others who share similar characteristics. Context signaling is used across a variety of types of self-description, including ethnicity (*"I'm Asian and this product makes my eyelashes look beautiful.*), sexual orientation (*"I'm gay and these tips definitely apply to the dating site I'm on*), and age (*"I'm sixty-eight, and I loved this. Highly relevant to people my age."*).

Theme 2: Self description as evidence of product quality Self-descriptions are often meant to directly support opinions about product quality, mostly by allowing the author to hold themselves as an example. For example, *"I was stuck at 160 lbs. [Health product] helped curb my appetite significantly while doing intense workouts. I have* lost 6 pounds and 2 sizes *to date."* and *"I got this book last year for school, and now I'm a database professional!"* both provide testimony to the effectiveness of a product with respect to the reviewer's personal description.

Theme 3: Self description as expertise or relevance Reviewers often signal their expertise, experience or background to indicate that they are particularly qualified to provide an opinion about a product. While statements in Theme 2 use descriptions to indicate experience with the product, the statements in Theme 3 are more about independent life experiences. For example, *"I am an experienced doctor, and confident about my skills"* provides evidence of expertise via the educational and professional experience of the reviewer, to influence readers to value the opinion. Other statements are less about formal training, and more about life experiences, including *"This is a true story about the war in the Pacific. I served my country as a Marine and can verify the authenticity."* This type of self description is frequent in reviews of media products (such as books and movies) where reviews often range more broadly into subjective opinions where a person's expertise or background may be relevant.

Theme 4: Self description as support for personal storytelling This type of motivation was also studied by Karampournioti and Wiedmann (2021) and corresponds to self descriptions used as part of disclosed stories about the reviewer's life. For example: *"I'm happy I bought this book. I'm a Muslim, but after immigrating to the United States, I have become skeptical of how the Western worldview fits with my beliefs."* This review shares personal history as a key part of the reviewer's story as they relate to the particular book. Like Theme 1, these narratives play a role in contextualizing products, however they are less product-focused and more about revealing personal details about the reviewer's past. Another example is this review of a medical product *"I've experienced bad allergies because of changes in the temperature over the last month. I'm from Tennessee, and my eyes have been scratchy and just really irritated. After I used these [product name] the first time I could immediately feel a difference."*

Theme 5: Self description as support for social commentary Some reviews engage in social commentary inspired by their interactions with the product. For instance, we observe reviewers promoting a religion, discussing racism or gender discrimination, and educating others about political and social issues. For example, the following from a book review: *"There is more racism and injustice than ever in America. I am white and served my country alongside African Americans. We have reached a tipping point in many different areas. Can't we agree to stop the hate?"*

8 Discussion

Self-description in e-commerce differs from traditional self-description previously studied in social media. In social media and other similar online forums people self-describe for the purpose of connecting to other people or building a community. Using thematic analysis to learn about reviewers' reasons for sharing about themselves, we find that self-descriptions in reviews are often written directly in service of product assessments. In particular, we find that reviewers describe themselves in order to better contextualize their product use, signal their expertise or authority with respect to their opinion, or to provide more details for a testimonial. In these ways, self-descriptions contribute to the quality and diversity of reviews with additional information about specific personal and product attributes that directly speak to individual experiences. This stands in contrast to the findings from related work in other domains (e.g., social network websites or online profiles (Ma et al. 2017; Wang, Burke, and Kraut 2016; Gamzu et al. 2021)), where the user's motivation to share information is oriented towards building relationships or attracting attention from other users.

One interesting finding is that there is evidence that self description increases the perception of review helpfulness. This makes sense when considering that the self description is often directly related to the product, and it covers the type of information not typically available from the product description, title, and images. With respect to star-ratings, people are less inclined to disclose information when reviewing products they rate lower. This may be because unsatisfactory products are viewed as universally poor in which case the reviewer's personal experience or context is not relevant, or it may be that people are less inclined to identify themselves when saying uncomplimentary things, because it is viewed as less socially acceptable.

Mining reviews for customer information is more reliable than other types of customer profiling, as the review is a snapshot of the customer attributes at the time the review was written. Customer attributes may change. Pregnant people become people with young children, and parents of young children become parents of adult children. But the customer review preserves the original relationship between the customer's context and a product. A review for cloth diapers from a new parent who is interested in sustainable products is still a relevant self-description even after the baby has outgrown the need for diapers.

It would be interesting to investigate which forms of self description change in time, and which persist. For example, the new parent interested in sustainable diapers will only need diapers for a few years, but may be interested in sustainability for the rest of their life.

E-commerce sites might allow users to explicitly filter or re-rank reviews based on particular user characteristics in order to more easily find reviews from other similar customers. This would allow customers to access information about a product that is not typically available from the manufacturer or the seller: Is it good for allergy sufferers? Do teenagers love it? Is it easy to open for people with arthritis? These considerations are among the most important considerations when making a purchase, and other customers are usually the only source for this type of information.

Quantitative analysis. We investigated whether it is possible to analyze and obtain actionable findings from automatically labeled self-descriptive reviews with the goal of scaling existing manual evaluations to obtain quantitative observations. We relied on classification models for this task and investigated the hypothesis that reviews with self-descriptive statements are more useful to customers, using regression analysis to predict votes of "this review is helpful". We found that most categories of self-descriptions in our taxonomy are predictive of helpful votes, though some more than others. For instance, we observed strong positive effect size for age, appearance, and medical condition, while we see much smaller effects for gender, hobbies, and relationship, and no statistically significant effect for location. One possible implication of this analysis is that there is a sweet spot for the degree of "personalization" reviews provide through self-description. Some categories (e.g., location) may be useful to very few customers, while others (e.g., gender) may match with too many. Further, some product types attract a wide variety of personal information (e.g., Books reflects nearly every self description category), other product types attract only a few categories (e.g., Apparel reflects primarily appearance and relationship). It is possible categories with the highest effect sizes (e.g., medical conditions and age) match with enough readers to be widely applicable, but are specific enough to provide useful, contextual product insights. It remains future work to identify the factors of a self-description, and the match between the reviewer and the reader, as in (Shin et al. 2017), to better predict review utility in context.

Limitations. Amazon reviews are not necessarily representative of product reviews on different e-commerce sites. Although we have chosen a variety of product types to understand where and how different types of self-description occurs, other sites may offer very different shopping experiences or user interfaces that affect how reviews are written. In addition, our study is restricted to reviews written in English from the United States. We have no information about the demographics of the authors of the reviews, hence no information about their potential biases, which may be present in the data. We leave to future work investigation of the degree to which design, language, and cultural differences affect the type, quality, and quantity of self-descriptions in product reviews.

We studied a fixed time period, and did not study the evolution over time of self description in reviews. This work is exploratory and relies heavily on qualitative methods to make sense of large amounts of user-generated text. We used "this review is helpful" votes as a proxy for review perceived helpfulness, but these votes are not a perfect representation of review utility. Furthermore, as mentioned in Section 6, the output of the classifiers is noisy and produces some incorrect labels. We addressed this by conducting a comparative analysis (in the Appendix) to evaluate the reliability of quantitative approaches.

9 Conclusions

E-commerce product reviews sometimes contain self descriptive statements that share information about the reviewer, such as their demographics, background, or interests. Reviews with self descriptions make up 12.7% of our random sample, but the observed frequency and type vary by the type of product being reviewed. In this paper, we contribute several results that together provide a broader under-

variable	baseline	SD binary	SD category
Intercept	7.03e-17	7.03e-17	7.03e-17
Length	0.2986*	0.3133*	0.2925*
Positive sentiment	-0.0691†	-0.0631†	-0.0578†
Negative sentiment	0.0124	0.0226	0.0036
Contain SD		0.0992*	
age			0.0374
appearance			0.0280
education			-0.0227
ethnicity			0.0343
gender			0.0154
location			-0.0007
medical condition			0.0867†
occupation			0.0235
personal hobbies			-0.0104
religion			0.0470
relationship			0.0317
DF	3	4	14
BIC	3622	3615	3676
Adj R-squared	0.102	0.111	0.111
Anova test F-stats		14.08554	2.23815

(a) Helpful votes

variable	baseline	SD binary	SD category
Intercept	1.40e-16	1.40e-16	1.40e-16
Length	0.0478†	0.0639†	0.0320
Positive sentiment	0.3480*	0.3545*	0.3829*
Negative sentiment	-0.0874†	-0.0763†	-0.1025*
Contain SD		0.1081*	
age			0.0411
appearance			-0.1049†
education			0.0364
ethnicity			0.0243
gender			0.0276
location			0.0615†
medical condition			0.1259*
occupation			0.1166*
personal hobbies			0.0094
religion			0.0631†
relationship			0.0389
DF	3	4	14
BIC	3563	3553	3542
Adj R-squared	0.141	0.152	0.197
Anova test F-stats		17.520708*	9.298403*

(b) Star rating

Table 5: Three standardized linear regression models predicting review helpfulness (Table 5a) and star-rating (Table 5b) using a manually annotated data set sampled from the Amazon.com dataset described in §3: a baseline model with no self-description features, a model with a binary self-description feature, and a model with per-category self-description features. Including self description categories significantly improved the fit of the regression model. P-value significance code $< .0001^{*}$ and $< .05^{\dagger}$

standing of the use, intent, and impact of self-descriptions in e-commerce reviews.

Reviewers often share personal details in direct support of a product recommendation, using the self-description to signal a context of use, expertise, or testimony. We found that readers find reviews that share personal details more helpful, as a regression analysis showed that nearly all categories of self-descriptions in our taxonomy are predictive of the review receiving more votes indicating helpfulness.

Given that self-descriptions are not common, we chose to identify self-descriptions at the review level. Future work could extend the self-description identification to extracting the descriptors from the reviews in aggregate at the product level. This would allow the e-commerce service to surface this information for the customer as an additional source of information about the product. We leave to future work to understand whether self-description increases the customer trust in a product or a review, and more detailed investigations into whether reviewers are more or less likely to use self-description in negative sentiment reviews.

Ethics Statement

This study shows that reviewers willingly and publicly disclose a wide variety of personal information. This information is in general non-identifying and intended to provide a practical service in relation to an opinion about a product. On their own, self-descriptions in reviews do not necessarily pose a privacy concern. Furthermore, self-descriptive information in reviews can be a noninvasive way of understanding customers, according to what they themselves are comfortable sharing.

However, the aggregation of multiple self-descriptive reviews at individual level could potentially lead to unintended disclosure of identifying data. We believe that privacy breaches in this manner, although highly unlikely, are not impossible. On one hand, this type of analysis is based on data which users voluntarily make public. Hence, reviewers have the choice to select what information they deem sensitive or not. On the other hand, self-descriptive information is quite sparse in review data, therefore providing useful information at product level aggregation, but very little information at individual level aggregation.

Nevertheless, our recommendation, which is in alignment with how this study was conducted, is to avoid user level information aggregation and focus on product level aggregation. This is, if reviewer level aggregation is discouraged, the risk of privacy breaches almost disappears, as self-descriptive information will then only remain associated to reviews and not to reviewers themselves.

Appendix

To complement our regression analysis on the full review set, we apply the same procedures to a set of 1300 manually annotated reviews. These annotated reviews were randomly sampled and collected independently from the classifier training data so as to minimize interleaving effects if any. The main difference between using the full review set and this one lies in how we obtain the SD signals, where the former is based on inferred classification results and the latter uses human assessment. The results are summarized in Tables 5a and 5b. Overall, we observe consistent trends across the two data sets, suggesting that the findings derived from the inference set are robust.

Specifically, SD category models (i.e., including all SD signals) best fit the respective dependable variables (i.e., helpful votes and star ratings) and achieve the highest R-squared scores. The coefficients suggest a more positive effect of SD compared to the inference set, although significance was found for only a subset of individual predictors. In predicting helpfulness votes, medical condition (0.0867) remains the most effective signal while location (-0.0007) appears to be less correlated. In predicting star ratings, the overall effect size tends to be larger compared to the inference set; meanwhile, medical condition (0.1259) and occupation (0.1166) stay consistently effective predictors with statistical significance.

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