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Why Did You Buy It? A Text Mining Approach to Understanding Purchasing Goals and Review Behaviors

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Completed Research Paper

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Abstract

Online reviews play a fundamental role in supporting purchase decisions and driving sales, but the sheer quantity and varying quality pose challenges for consumers to navigate. Using an unsupervised machine learning approach to extract latent topics from review texts, our paper demonstrates that shopping platforms can extract reviewers' original purchasing goals (profiles) varying in the degree of utility and hedonic orientations. These profiles significantly alter their review behaviors in terms of effort, complexity, sentiment, and rating decision. A follow-up experiment finds early evidence that future consumers perceive reviews that match their shopping orientation more favorably in terms of both argument quality and review helpfulness. The paper contributes a new approach to understanding reviewer behaviors and makes a practical recommendation to online shopping platforms to match reviewer and consumer purchasing orientations.

Keywords

e-commerce, online reviews, text analysis, Latent Dirichlet Allocation (LDA), topic extraction.

Introduction

It has been well documented by prior research that online reviews play an important role in helping consumers navigate the shopping process (Mudambi and Schuff 2010), as such it is a driving force behind website traffic and sales (Chevalier and Mayzlin 2006). To aid consumers in browsing among thousands of online reviews, platforms like Amazon often highlight "featured" reviews they deem quality. These highlights are often selected with criteria like reviewer status, review valence, and the helpful votes a review received (Wu 2017). Nevertheless, to the extent of our knowledge, virtually no platform provides an option to highlight reviews based on the reviewers' original purposes of purchasing.

Communicating about experiences with products or services is one of the key motivations for past consumers to generate online reviews (Rosario et al. 2020). In writing reviews, consumers communicate about their experiences with specific characteristics (Benbunan-Fich 2020). Therefore, reviewers with different purchasing goals, or the reasons for which they bought a product, likely differ in their expectation confirmation and subsequent review writing and rating behavior. For instance, individuals who bought smartwatches as fashion items would likely review about the products' cosmetic values, as they are relevant to what they expected and paid attention to in their experience phase. On the other hand, others who bought smartwatches for their functions would accordingly write reviews based on expectations and experiences with those functions. Consequently, it may prove counterproductive to platforms to highlight reviews communicating irrelevant sets of expectations and experiences to a new consumer who needs helpful information to help with a purchase decision.

In this paper, we aim at understanding (1) how review-writing and rating behaviors differ among reviewers with different purchasing goals ("profiles"), (2) how we may understand reviewer profiles from their reviews, and (3) how a (mis)match between consumer and review profiles influence consumers' evaluation of a review. We adopted Latent Dirichlet Allocation (LDA), an unsupervised machine learning approach, to uncover reviewer profiles, and conducted a number of analyses with some review behaviors of interest. We make a methodological contribution by demonstrating a helpful approach to understanding reviewers' profiles from review texts. We also make a theoretical contribution by examining how these profiles alter review behaviors. In the following section, we briefly review the literature, and introduce the methodological approach, before presenting our findings.

Literature Review and Hypotheses

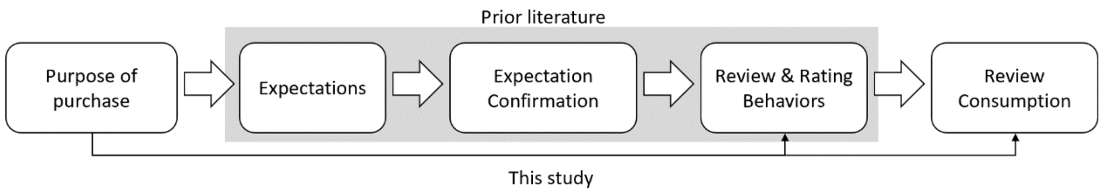

Figure 1. Theoretical Model

We consulted the theoretical underpinning of shopping behaviors and review-writing behaviors in two relevant literature streams to develop our theoretical model and hypotheses.

The first stream of the literature involves consumers' shopping focus and documents two fundamental orientations: utility and hedonic (Baker and Wakefield 2012). While utility orientation is cognitive, functional choices that cater to necessities, hedonic orientation describes the satisfaction of joy, fun, and other more subjective and personal values (Babin et al. 1994, Moore 2015). Though some consumers may express both orientations, they are often found to be either hedonic- or utility-oriented (Baker and Wakefield 2012). Such orientations influence shopping behaviors important to businesses, such as the intention to visit (Baker and Wakefield 2012) or to repeat a purchase (Chiu et al. 2014). In an online shopping context, consumers pay attention to utility, functional features as well as hedonic aspects that appeal to emotion like aesthetic performances (Liu et al. 2020).

The second stream of research documents customer satisfaction with shopping experiences as a key driver of online review behaviors. Specifically, experience with a product or service serves as a reference that consumers use to compare against the initial expectations about the product or service (Oliver 1980). This comparison affects customer satisfaction and drives post-purchase behaviors (Oliver 1980), including online review writing (Nam et al. 2020). Specific to shopping orientation in an online shopping context, failing to meet consumers' utility expectations and hedonic expectations significantly lowers their satisfaction (Chiu et al. 2014). Understandably, these dissatisfied consumers likely convey their unmet needs in their online reviews.

As consumers write about their experience with a product, its characteristics and whether they meet expectations are elaborated in online reviews' textual content, which is read by future consumers. For instance, Benbunan-Fich (2020) documented rich descriptions of a wearable device's feature failures in its online reviews. Nevertheless, these reviews are only perceived as helpful by a consumer if they provide information relevant to his or her specific decision making (Mudambi and Schuff 2010), which involves purchasing orientation, as in what the consumer looks for in the product. For instance, a consumer who is looking for utility features that serve specific needs may find reviews describing a hedonic experience, such as cosmetic quality, good look, and joy, irrelevant. On the other hand, a consumer with hedonic purposes, such as decoration, may deem the aforementioned reviews helpful.

Synthesizing the two literature streams, we posit that a misalignment between reviewers and current consumers' purchasing purpose risks reducing online reviews' positive impact for several reasons. First, as reviews are expressions of experience, a reviewer with different purchasing profiles may engage in different review writing and rating behaviors. Given a product with a blend of hedonic cosmetic values and utilitarian functions, we expect utility-oriented reviewers to use more complex language in order to describe the various functions of the product, compared to hedonic-oriented reviewers. This complexity in language will necessarily involve a greater number of words, therefore increase the review length with which reviewers expound on their thoughts (Vallurupalli and Bose 2020).

> **H1**: Reviewers with more utility-oriented profiles write reviews with (a) greater length and (b) more language complexity.

In terms of rating behavior, given the same product with both hedonic and utility values, a reviewer with a higher utility orientation may leave more favorable ratings for several reasons. First, among the various functions of the product, it is more likely that some features meet the utility-oriented reviewer's expectations and lead to a more favorable rating. Furthermore, we are limiting our analysis set to items that fall under the category of search goods; that is, goods whose qualities can be evaluated before purchase. Because these goods can be evaluated based on their merits and technical qualities, we expect that utility-oriented shoppers will seek out goods that conform to their needs. Second, utility shopping orientation is cognitive, and functional, and involves collecting information (Babin et al. 1994). Shoppers purchasing to meet specific necessities likely search, compare features across products, and purchase one that objectively fits them best (Mudambi and Schuff 2010).

> **H2**: Reviewers with more utility-oriented profiles (a) write more positively and (b) are more likely to give a positive rating.

Hypotheses H1 and H2 hold that reviewers with different profiles will engage in different review writing and rating behaviors for the same product. Separate from the reviewers and for similar reasons, we expect current consumers with their own orientation will perceive matching reviews as more helpful:

> **H3**: Consumers with higher utility orientation will perceive reviews with hedonic-oriented profiles (a) lower in argument quality and (b) less helpful.

To the extent of our knowledge, online shopping platforms (e.g., Amazon.com) use algorithms to highlight "featured" reviews based on the reviewers' status ("top reviewer" or "verified") or the number of helpfulness votes received (Wu 2017). Alternatively, they allow consumers to sort for the newest reviews or filter reviews by individual keywords that frequently appear. As a result, we also propose a computer-assisted, automated approach to uncover reviewer profiles contained in the review text to enable current consumers to filter for reviews with the relevant profiles, not just the keywords.

Computer-assisted text analysis techniques are able to uncover useful insights from a large quantity of data in a relatively objective manner (Adamopoulos et al. 2018). For instance, the dictionary methods have been applied to extract various emotions (Yin et al. 2014), personality traits, and review sentiments (Adamopoulos et al. 2018) from the textual content. Automated approaches, such as topic extraction or topic modeling, are recently applied in IS studies involving unstructured data (Abbasi et al. 2018; Shi et al. 2016). On top of the advantages listed above, topic modeling using unsupervised machine learning does not impose strict, predefined rules, therefore can uncover underlying topics based on the natural patterns of words (Humphreys and Wang 2018; Shi et al. 2016). The following section describes our data collection, analytical approach, and initial results.

Study 1: Reviewer Profiles and Behaviors

Data Collection

We collected a sample of more than 2500 online reviews for smartwatches from Best Buy. The selection of the product was a deliberate choice that balance utility and hedonic goals. Besides serving specific utility needs such as notifications, sport, and activity tracking, smartwatches are also fashionable items that serve hedonic purposes. Additionally, BestBuy is an appropriate platform because they apply a binary rating scale asking if a reviewer would recommend a product or not. We deem this recommendation mechanism more suitable for our purpose, compared to the common five-star rating scale, as the latter suffers from serious rating biases and inflation that makes the distinction between positive and negative ratings obscure in the mid-range of the scale (i.e., 2 or 3 stars) (Breinlinger et al. 2019). After filtering out the observations that are the sellers' replies to original reviewers, we are left with 2296 usable reviews for 74 products.

Reviewer Profile Extraction

We first explain how the reviewer profiles were extracted using an unsupervised machine learning approach for topic extraction, before describing other measurements in the next section. The paper adopts an unsupervised machine learning method, Latent Dirichlet Allocation (LDA) to uncover underlying topics in the textual reviews. LDA is a parsimonious approach to the analysis of latent topics in textual data (Blei et al. 2003). LDA holds that the probability of a word's appearance in a document (i.e. a product review) is dependent on the presence of the topic it represents in that document. As a result, LDA extracts a topic based on the unique probability vectors of words representing the topic (Büschken and Allenby 2016). For an in-depth introduction to the technicality of LDA, we would refer readers to Tirunillai and Tellis (2014). The analysis was conducted in Knime software version 4.2.

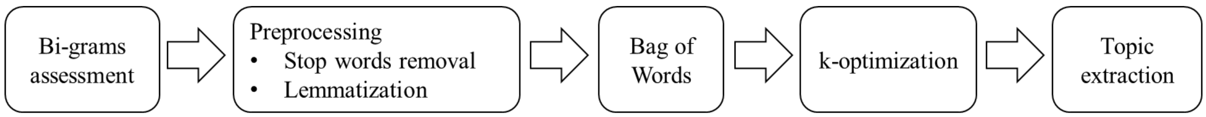

Figure 2. Topic Extraction Procedure

Several document preparation steps were taken before topic extraction, including bi-gram assessment, preprocessing, and creating bags-of-words (BoW). Bi-gram is a specification of N-gram that creates pairs of every two words in a document. Frequently occurring word pair that could be meaningful for analysis was combined into a single compound word (i.e. "heart rate" to "heart-rate") to avoid losing their combined meaning in later steps. Next, the reviews went through part-of-speech tagging, in which each word was given tags for its role in the sentence either as a verb, noun, adjective, and so on. For the purpose of this project, because topics are most likely represented with nouns and noun phrases, only words with the "noun" family tags went on to preprocessing. In preprocessing, stop words (i.e. "a", "the", "of") were removed before the remaining words were lemmatized to their original forms based on the Stanford Core Natural Language Processing (NLP) library. Next, BoWs were created to individualize words from each review, which allowed for subsequence analyses using terms' occurrence frequencies and their connections to topics. Terms appearing less than twice in the whole dataset were deemed infrequent terms and not included in the optimization to identify the number of topics (k-optimization).

As LDA is a probability-based topic extraction method, k-optimization was conducted using the elbow method. This method determines the number of topics at which the joint probability of topics and words (measured in log-likelihood) stop improving noticeably. Specifically, a series of possible values for k from 1 to 40 are tested, and the parameters α (represents the document to topic distribution) and β (representing the topic to word distribution) were respectively set at 0.1 and 0.01, following the general recommendation in the text analysis literature (Steyvers and Griffiths 2006, Kaplan and Vakili 2015, Huang et al. 2018).

Dependent Variable Measurements

We operationalize the review writing and rating behaviors with observed variables in the dataset. First, review complexity is measured by calculating the average number of words used per sentence, as longer sentences are typically more complex than shorter ones (Vallurupalli and Bose 2020). Second, review length was measured by word count (Yazdani et al. 2018). Third, review sentiment, or how positively or negatively a reviewer writes, is operationalized using the ANEW dictionary (Humphreys and Wang 2018; Nielsen 2011) to calculate the valence of a review based on the number of positive and negative words it contains. A higher sentiment score suggests more positive sentiment. Last, review ratings are represented by each review's recommendation choice, in which a "yes" stands for a positive rating, and a "no" encodes a negative rating. As stated earlier, this is a preferred proxy to the common five-star rating scale, as it allows us to observe a reviewer's definitive positive or negative choice.

Results

Reviewer Profiles

The optimization process resulted in 4 interpretable, little-overlapped latent topics. Based on the term frequency, the topic extraction process assigned to each review the probability that it belongs to the four topics. Each review is then assigned the topic with the highest probability. The most frequently appeared 15 terms for each topic, which are presented in the word clouds in Figure 3, help us interpret the reviewer profiles.

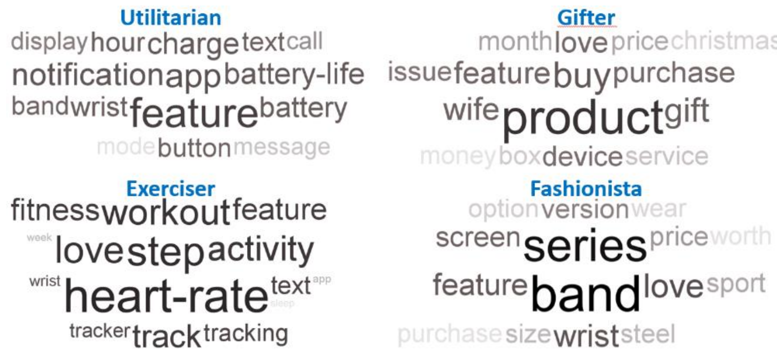

Figure 3. Topic Term Word Clouds

These word clouds represent 4 distinctive reviewer profiles, namely *Utilitarian*, *Gifter*, *Exerciser*, and *Fashionista*. The *Utilitarian* profile is characterized by terms representing basic functions of the products (i.e., feature, app, notification) that help consumers in their day-to-day activities like messaging, texting, and calling, which are also mentioned in the most frequent terms for this topic. Users in the *Gifter* profile typically bought the product for their loved ones (i.e., wife) as gifts for special occasions (i.e., Christmas), and thus they pay attention to value (i.e., money), and post-purchase services. The *Exercisers* emphasize workout-related features of the product such as heart-rate monitors and trackers, and they discuss how those functions help their fitness activities too. The *Fashionista* profile is represented by terms referring specifically to value (i.e., price, worth) cosmetic elements like material (i.e., steel), look (i.e., size, band), and others (i.e., version, option).

These four profiles match well with our expectation of utility-oriented versus hedonic-oriented consumer types. The *Exerciser* group appears to be the most utility-oriented, seconded by *Utilitarian*. *Fashionista* is the most hedonic-oriented group. Nevertheless, *Gifter* reviewers appear to go either way, as they may have bought the product for a hedonic-focused or utility-focused and have written reviews accordingly. These categorization results enter the initial hypotheses testing as hierarchical categories (with *Exerciser* chosen as the reference group). With reviewers subdivided into hierarchical categories, we leverage mixed-effects methods for analysis, including random intercepts (to allow for differences in baseline measurements between groups) as well as random slopes (to allow for differences in response to treatment).

Reviewer Behaviors

For an initial analysis, we specified mixed-effects models controlling for the random effects of products and reviewers using the R package *lme4*. The model also allows for the review profile to randomly vary within each product. We followed up with pairwise contrasts to compare the behavior differences across profiles, using the R package *emmeans*. To test H1a, H1b, and H2a, review complexity, length, and sentiment were respectively regressed against reviewer profiles, after controlling for product and reviewer effects. Due to their distribution, review complexity and length are log-transformed. Last, H2b was tested with a mixed-effects logistic regression which specified the recommendation choice (1 is *yes*, 0 is *no*) as the binary dependent variable (DV) and incorporated the same set of independent variables (IVs). The regression and contrast results in Table 1

Dependent Variable	Log_{10}(Complexity)		Log_{10}(Length)		Sentiment		Recommend***	
Fixed Effects	Est. (S.E.)	*p*	Est. (SE)	*p*	Est. (S.E.)	*p*	Est. (S.E.)	*p*
(Intercept)	1.13 (.01)	**<.01**	1.68 (.02)	**<.01**	6.36 (.24)	**<.01**	3.29 (.34)	**<.01**
Gifter	-.05 (.02)	**<.01**	-0.12 (.02)	**<.01**	-.86 (.33)	**.01**	-1.04 (.28)	**<.01**
Fashionista	-.03 (.01)	**.01**	-.09 (.02)	**<.01**	-.33 (.34)	.34	-.57 (.29)	**.05**
Utilitarian	.04 (.02)	**.05**	.21 (.05)	**<.01**	1.39 (.83)	.10	-1.01 (.37)	**.01**
Random Effects*		S.D.		S.D.		S.D.		S.D.
Grouping: Reviewer								
(Intercept)		.11		.17		1.96		.73
Grouping: Product								
(Intercept)		.01		.13		.88		1.03
Slope-Fashionista		.57		.06		.36		.34
Slope-Gifter		.02		.07		.53		.46
Slope-Utilitarian		.05		.26		4.40		.91
Pairwise contrasts**	Difference	*p*	Difference	*p*	Difference	*p*	Difference	*p*
Exerciser – Fashionista	.05	**.02**	.12	**<.01**	.86	**.04**	1.04	**<.01**
Exerciser – Gifter	.03	.06	.09	**.01**	.33	.78	.57	.21
Exerciser – Utilitarian	-.04	.21	-.21	**<.01**	-1.39	.34	1.01	**.03**
Utilitarian – Fashionista	.08	**<.01**	.33	**<.01**	2.25	.06	.03	1.00
Utilitarian – Gifter	.07	**.02**	.30	**<.01**	1.72	.23	-.44	.52
Fashionista – Gifter	-.02	.70	-.03	.49	-.53	.47	-.47	.23
*Observations: 2296, products: 74, reviewers: 2070; **Pairwise contrast results are Tukey-adjusted; ***Binary DV								

Table 1. Mixed-effects Regression and Pairwise Contrast Results

The regression models and follow-up contrasts show noticeable differences between reviewer profiles in the hypothesized directions. Specifically, in terms of review complexity, a reviewer with more utility-focused profiles like *Exerciser* and *Utilitarian* writes more complex reviews than *Gifter* and *Fashionista*. Also, *Exerciser* and *Utilitarian* reviewers write longer reviews than *Gifter* and *Fashionista*. H1a and H1b are supported. In terms of sentiment and recommendation, *Fashionista* reviewers write in less positive sentiment than *Exerciser* and (marginally) *Utilitarian*. There is no significant difference between *Gifter* and the utility-focused profiles. In terms of recommendation decision, *Exerciser* reviewers will have a higher log-odds of recommending the product, compared to *Exerciser* reviewers. As a result, H2a and H2b are partially supported. Interestingly, there is an unexpected effect in the significantly greater likelihood that an *Exerciser* recommends the product than a *Utilitarian*.

Study 2: Consumer Perceptions

Data Collection

To provide a pilot test for H3a and H3b, we conducted a repeated-measure online experiment on Amazon Mechanical Turk (MTurk) with 40 participants who will rate four reviews selected from study 1 to represent the four profiles, after controlling for similar word count and complexity. The experiment proceeded as follows. First, participants provided their demographic information and shopping orientation. Then, they were asked to imagine shopping for a generic smartwatch and using reviews to make a decision. Each participant saw four reviews in a fully randomized order and rated the argument quality and helpfulness for each review.

Measurements

Constructs are measured using question items from established and validated sources, and all items used a 7-point Likert-like scale. First, shopping orientation scales are adapted and modified from the seminal work of Babin et al. (1994) to capture both utility and hedonic orientations. To streamline the pilot analysis of a small sample, we calculated general shopping orientation by subtracting average hedonic orientation from average utility orientation. The greater the orientation value, the more utility-oriented a participant is. Second, argument quality was measured with scale items adapted from Sussman and Siegal (2003) and modified to suit the study context. Last, review helpfulness was operationalized as a question item "*Do you find this review helpful?*", which is commonly used on shopping platforms (i.e., Amazon).

Results

To analyze the pilot data, hierarchical linear models were configured to account for subject-level shopping orientation and random effects, and estimate the fixed, review-level effects of the review types. Similar to study 1, these models also allow for the review types to have random slopes across subjects. For each dependent variable, we compared two models, without versus with the interaction effects between review types and shopping orientation. The interaction effects indicate whether a shopping orientation influences the perception of review in each type. Specifically, as a high value in *Orientation* indicates a person is utility-oriented, a significantly positive interaction between *Orientation* and a profile means that a utility-oriented consumer favors that profile. On the other hand, a significant but negative interaction between *Orientation* and another profile suggests that a utility-oriented customer disfavors that profile. The models with the interactions configured consistently outperform ones without interactions for both argument quality (marginal R^2 increased from .10 to .16) and review helpfulness (marginal R^2 increased from .06 to .12).

Dependent Variable	Argument Quality				Review Helpfulness			
	Model 1		Model 2**		Model 1		Model 2**	
Fixed Effects	Est. (S.E.)	*p*	Est. (SE)	*p*	Est. (S.E.)	*p*	Est. (S.E.)	*p*
(Intercept)	5.93 (.11)	**<.01**	5.93 (.11)	**<.01**	5.89 (.14)	**<.01**	5.88 (.14)	**<.01**
Fashionista	-.56 (.23)	**.02**	-.52 (.22)	**.02**	-.68 (.28)	**.02**	-.63 (.27)	**.02**
Gifter	-.75 (.23)	**<.01**	-.74 (.23)	**<.01**	-.53 (.25)	**.04**	-.52 (.25)	**.04**
Utilitarian	-.36 (.17)	**.04**	-.36 (.17)	**.04**	-.43 (.20)	**.03**	-.41 (.20)	**.04**
Shopping Orientation	-.09 (.03)	**.01**	-.07 (.04)	.09	-.08 (.04)	.07	-.04 (.06)	.54
Orientation*Fashionista	-		-.19 (.09)	**.04**	-		-.23 (.11)	**.04**
Orientation*Gifter	-		-.04 (.09)	.63	-		-.02 (.10)	.87
Orientation*Utilitarian	-		.03 (.07)	.71	-		-.06 (.08)	.45
Random Effects*		S.D.		S.D.		S.D.		S.D.
(Intercept)		.51		.51		.73		.72
Slope-Fashionista		1.31		1.23		1.63		1.53
Slope-Gifter		1.28		1.28		1.39		1.39
Slope-Utilitarian		.87		.87		1.01		1.01
Marginal R^2		.10		.16		.06		.12

*Observations: 160, subjects: 40
**Model expansion by including subjects' Age, Sex, and Income was tested but did not improve the model significantly.

Table 2. Mixed-effects Regression and Pairwise Contrast Results

The models show significant effects from the review types when compared against the reference group (*Exerciser*). Overall, compared to *Exerciser*, consumers found other review types lower in argument quality and less helpful. The coefficients of interest, however, are the interactions between consumers' shopping orientation and review profiles. Positive values in these cross-level interactions indicate a preference for a profile attributable to a consumer being more utility-oriented, while negative values indicate disfavor of a profile due to such a utility focus. The results show negative and significant interactions between orientation and fashionista variables in both DVs. In other words, a utility-oriented consumer (higher in Orientation) will rate *Fashionista* review more unfavorably in terms of both argument quality and review helpfulness.

Discussion, Future Plan, and Conclusion

Our analyses of small sample datasets provide early evidence to support the premise of the paper. We posit that it is beneficial for online shopping platforms to extract reviewer "profiles" from their written texts to help consumers easily find reviews that better meet their needs, therefore are more helpful. In the first, archival study, we adapted an unsupervised machine learning technique to uncover hidden reviewer profiles in the textual content of the reviews. These profiles demonstrate a reviewer's shopping orientation that influences their review and rating behaviors. In detail, we found that more utility-oriented reviewers write longer and more complex reviews. They are also more positive in both their written sentiment and rating choice. In the second, experimental study, a consumer who is more utility-focused indeed displayed a preference toward review types that match their orientation, and disfavored hedonic-oriented reviews.

The potential contribution is threefold. First, the paper proposes an approach to understanding reviewers' shopping orientations as reflected in their written reviews. Second, we also contribute to the online review literature by exploring the influences of shopping orientation (profiles) on subsequent review and rating behaviors and how future consumers discriminate between these profiles. Third, the findings are of practical relevance to online shopping platforms and e-commerce businesses, which can benefit from tailoring highlighted reviews to match current consumers' shopping purposes or allowing consumers to filter for reviews that match their profiles.

The current research is not without limitations. First, despite having over 2,000 observations, the dataset is still a narrow sample of a single product category (smartwatch). However, this small sample is efficient for us to test the feasibility of the research-in-progress, and a future plan is in place to include additional product categories and reviews for robustness. Second, more aspects of the written reviews documented in the literature, such as embedded emotions, are not addressed in this current work. Third, while the differences between the uncovered reviewer profiles generally support the hypotheses, some profiles need further examination. For instance, *Exerciser* and *Utilitarian*, while both are utility-oriented, have differences in review length and rating choices. *Gifter* profile, on the other hand, requires further examination of its true orientation, as a purchaser of gifts may select it with a recipient's utility or hedonic needs in mind, or both. Further analysis taking into account various review characteristics may shed light on these groups' differences or lack thereof. The next phase of the project with more expansive data and thorough analysis is currently planned.

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