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What impacts the helpfulness of online multidimensional reviews? A perspective from cross-attribute rating and ranking Inconsistency

Completed Research Paper

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Abstract

This paper proposes investigations of the effects of information inconsistency, particularly ranking inconsistency, on the review helpfulness in a multidimensional rating system, based on information diagnosticity and attribution theory. The insight findings of this paper are: (a) The product cross-attribute dispersion has a significant negative impact on review helpfulness, while the overall attribute ranking consistency and the ranking consistency of the product's best prominent attribute positively impact review helpfulness. (b) The product cross-attribute dispersion negatively impacts the review helpfulness for non-luxury products but it positively impacts that for luxury products, while the cross-attribute rating difference of a single review positively impacts it helpfulness only if the product is non-luxury. (c) The overall attribute ranking consistency significantly impacts the review helpfulness only for luxury products, whereas the ranking consistency of the product's best and worst prominent attributes impact the review helpfulness only for non-luxury products.

Keywords: Online reviews, multi-dimensional ratings, information inconsistency, diagnosticity

Introduction

Most e-commerce platforms (e.g., Amazon.com, Tripadvisor.com) provide a reviewing platform for consumers to post their ratings and comments on the products they have bought. Online reviews enable consumers to interact with others in addition to providing a general summary of a product. People can post reviews to share the usage experiences of products or services, advocate their own values, and enhance socialization (Qin et al, 2022). According to Bright Local's survey in 2022, 76% of consumers "always" or "regularly" read online reviews when browsing local businesses (Rosie, 2022). It has been reported that online reviews can help consumers reduce the stress of information overload and play an important role in influencing their attitudes toward products and purchase decisions (Jabr and Rahman, 2022).

With the advancement of internet technology, consumers can conduct a comprehensive examination of product quality by accessing a vast number of online reviews, which can reduce uncertainty when making product purchasing decisions (Mudambi and Schuff, 2010). In addition to single overall rating systems (herein referred to as "SD systems"), there are multidimensional rating systems ("MD systems") that are also emerging. MD systems help buyers better grasp how well a product performs across different aspects. For instance, in some car review websites like Edmunds.com and Autohome.com, consumers are able to rate and review based on car attributes including safety, performance, interior, comfort, etc. MD reviews help subsequent consumers better align their preferences with product attributes and make precise purchasing decisions (Schneider et al., 2021).

In light of the growing use of MD systems in practice, some recent studies investigated the value of MD systems. According to (Chen et al. 2018), a same merchants' overall ratings on a MD system typically are higher and exhibit an upward trend than on a SD system. Schneider et al. (2021) conducted various experiments to control when and how consumers offer multi-dimensional and overall ratings, and they discovered that the design of the MD systems has a significant impact on user rating behaviors. Tunc et al. (2021) explored how SD and MD systems affect consumers' perceptions of competitive products. Researchers have also investigated the connection between multidimensional ratings and product sales when more granular evaluations are displayed to consumers in MD systems (Zheng et al., 2018; Zheng et al., 2022; Liu et al., 2022). Focusing on the effect of MD ratings on review helpfulness, however, only the study of (Kong et al., 2020) indicated that the ratings on functional dimensions and the ratings on hedonic dimensions have different effects on consumer informed helpfulness. Given that online review helpfulness is one of the main indicators to measure the quality of reviews (Mudambi and Schuff, 2010; Sun et al., 2019), and that consumers usually adopt reviews with high helpfulness as guidelines for purchase decision making (Mudambi and Schuff, 2010; Huang et al., 2013; Eslami et al., 2018), investigating how multidimensional ratings influence online review helpfulness will be also essential in establishing the value of MD ratings systems.

From the perspective of online review measurements, information inconsistency is usually regarded to be able to impact how helpful an online review is (Yin et al., 2016). The theory of information diagnosticity is usually adopted to explain this impact -- high rating inconsistency expresses a distinguishing opinion of the reviewer and it is therefore more diagnostic for consumers if other information is difficult or ambiguous to judge (Li, 2018). Rating inconsistency refers to the difference between a reviewer's rating and the product's average rating in traditional SD systems. In MD systems, however, we argue that inconsistent information can be measured or be perceived by consumers in different ways.

We conclude that the first type of information inconsistency in MD systems is the difference between the multidimensional ratings. A reviewer may issue inconsistent multidimensional ratings to a product and this behavior represents a clearer preference comparing to issuing only an overall rating. This type of rating variation across certain dimensions is typically measured in product level, i.e., the difference between the averagely multidimensional ratings of a product, and it has been reported to be able to impact consumer buying behaviors as well as product sales (Zheng et al., 2018; Zheng et al., 2022; Liu et al., 2022). In addition, Kong et al. (2020) discovered that the difference between functional attribute ratings and hedonic attribute ratings will influence review helpfulness, but they do not examine the overall measurement of the variation of multidimensional ratings.

We also take into account the variation in reviewers' rankings on product attributes as another type of information inconsistency in MD systems. In an MD system, consumers can also observe the ranking order for product attributes besides rating values, and they might perceive the inconsistency between a single reviewer's ranking and the overall ranking on the attributes of a product. For example, given that one product's top-rated dimension (attribute) is A according to the average ratings of all reviewers, while in a single reviewer's multidimensional ratings it is ranked at the bottom; this demonstrates a clear inconsistency between this reviewer's assessment and that of others regarding the best dimension (attribute) of the product. Inconsistent ranking may also be perceived by consumers based on the overall impression – to compare a reviewer's ranking order on all attributes with others' overall ranking order of a product. For another example, assume the overall ranking of a product's attributes from the best to the worst is [A, B, C, D] based on the average ratings, and two single reviewers' rankings are [A, B, D, C] and [D, C, B, A], respectively, consumers would easily observe that the former reviewer's ranking is with higher consistency to the overall rankings, while the latter one is with lower ranking consistency. To our knowledge, such cross-attribute ranking (in)consistency has not been investigated before.

This study aims to investigate the effects of information inconsistency, particularly ranking inconsistency, on the review helpfulness in a multidimensional rating system. It will contribute to both expanding the measurement of multidimensional reviews and improving the design of online review systems. The moderating role of product types in terms of premium and ordinary products is also investigated in this study. Literature has demonstrated that the impact of inconsistent information on review helpfulness differs for premium and ordinary products (Chen, 2016; Kong et al., 2020, Zheng et al., 2022). Firms usually implement premium and ordinary product differentiation strategies to cater to different markets (Kastanakis and Balabanis, 2012). According to Kong et al. (2020), because consumers have different concerns about product attributes for premium and ordinary products, they may also value those attributes differently. Following existing studies, we conduct analysis and experiments on premium and ordinary products, to investigate the impact of rating and ranking inconsistency on review helpfulness in MD systems. The main questions expected to be answered in this study are:

(a) Does the cross-attribute rating inconsistency information impact the helpfulness of multidimensional online reviews?
(b) Does the cross-attribute ranking inconsistency information impact the helpfulness of multidimensional online reviews?
(c) How does the product type (premium vs. ordinary) moderate the impact of cross-attribute rating and ranking inconsistency on multidimensional online review?

We construct our model based on information diagnosticity and attribution theory. A real automotive multidimensional review dataset with 8,281 consumer review messages for 226 car models is crawled for empirical analyses. The results demonstrate that cross-attribute rating inconsistency generally negatively impact the helpfulness of multidimensional online reviews. In terms of cross-attribute ranking information, we find that the consistency of the overall attribute ranking order and the best prominent attribute are found to have positive impacts on multidimensional review helpfulness. Moreover, product type moderates these effects: the positive impact of the overall attribute ranking consistency is more significant for premium products such as luxury cars, while the positive impacts of the ranking position of the product's best and worst prominent attributes are more significant for ordinary products such as non-luxury cars. Our research firstly demonstrates that both the cross-attribute rating and ranking information influence consumer perceiving the value of online reviews. It also develops new cross-attribute ranking measurements for multidimensional reviews, which are believed to be with significances for online review system design and management practices.

Theoretical Foundations and Hypotheses

Online Review Helpfulness

Online review platforms are one of the most popular e-commerce social media tools today. Most e-commerce sites use a voting system to evaluate which reviews are helpful to consumers. This is because review helpfulness votes can help users decide which reviews to use to make product purchase decisions (Lee et al., 2021). Previous studies on review helpfulness have focused on the effects of various factors in single-dimensional review systems. These factors can be summarized to review characteristics, reviewer characteristics, and product characteristics. Review characteristics include the number of reviews, average rating, word-of-mouth dispersion (Lee et al., 2021), extreme reviews (Mudambi and Schuff, 2010), review inconsistency (Yin et al., 2016), and the propensity of reviews (one-sided or two-sided) (Chen, 2016), etc. Reviewer characteristics include reviewer expertise (Choi and Leon, 2020), reviewer non-anonymity (Forman et al., 2008), etc. Product characteristics include product type (Siering et al., 2018; Chen, 2016), product diversity (Choi and Leon, 2020), etc. Mudambi and Schuff (2010) conducted an empirical study of user reviews on Amazon.com from a perception theory perspective and showed that review helpfulness is mainly influenced by review depth, review polarity, and product type. Siering et al. (2018) showed that higher levels of expertise were associated with higher ratings and received fewer votes for review helpfulness when the identity of the reviewer was non-anonymous. It can be concluded that existing studies have established a comprehensive structure of online review helpfulness for SD systems. In contrast, only a few researchers have investigated how multidimensional ratings affect review helpfulness in MD systems. Kong et al. (2020) suggested that a positive rating of functional attributes and a negative rating of hedonic attributes were more helpful for ordinary products, while a positive rating of hedonic attributes was more helpful for premium products. Their research helps companies better understand the heterogeneity of consumer preferences for functional and hedonic attributes across product types.

Multidimensional Rating Behavior

Regarding the research of multidimensional reviews, there have been emerging studies focusing on exploring the value of MD systems and the differences between SD and MD systems from the perspectives of reviewing system design and user rating behaviors (Chen et al., 2018; Schneider et al.，2020; Tunc et al.，2021). Chen et al. (2018) firstly pointed out that consumers' rating behaviors vary in SD and MD systems. The average ratings to a single merchant in an SD system generally decrease over time, whereas in a MD system, the ratings show an upward trend. Subsequently, Schneider et al. (2020) conducted comprehensive experimental analyses and found that dimensional ratings in MD systems influence user overall ratings based on how the dimensions have rated. By developing a game theory model, Tunc et al. (2021) found that increased review dimensionality enhances the advantage of multidimensional rating systems when firms' product differentiation was high. There are also studies investigating the effects of multidimensional rating systems on consumers' perceptions and behaviors (Zheng et al., 2022; Zheng et al., 2018; Kong et al., 2020). Zheng et al. (2018) divided the dimensional attributes of products into vertical and horizontal attributes and explored their different moderating effects in the impact of cross-reviewer rating variation on product sales. Their study showed that higher cross-reviewer rating variations have a significant negative impact on sales only when the product dimensions are vertical. Zheng et al. (2022) also revealed that the cross-dimensional rating variation impact the sales of mainstream and niche products differently. The study of Kong et al. (2020) is mostly related to our study, and it suggested that review helpfulness as well as product sales are influenced by rating variation between functional attributes and hedonic attributes.

Research Model and Hypotheses

The information richness of multidimensional rating systems can make it more difficult for consumers to make purchase decisions. When consumers are unable to accurately assess the quality of online reviews, they seek more diagnostic cues (Chen, 2016), including rating differences between dimensions, inconsistent opinions among reviewers, and product characteristics. Focusing on the information inconsistency, we construct a concept model based on the information diagnosticity and attribution theories in Figure 1.

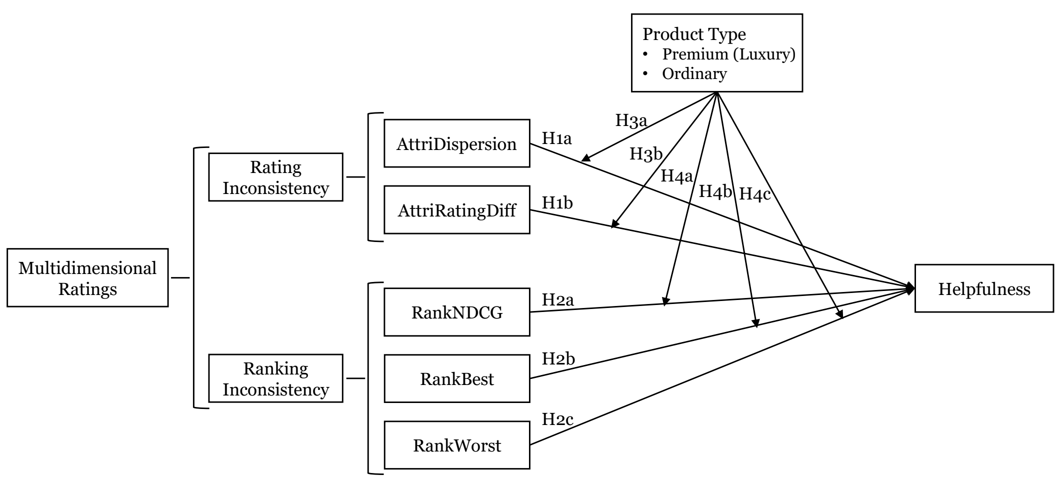

Figure 1. Conceptual Model

Cross-attribute rating and ranking inconsistency are the two categories under which we classify the information inconsistency caused by multidimensional ratings. Cross-attribute rating inconsistency refers to the rating variation across various product attributes, which was also called cross-dimensional or inter-dimensional rating variation in previous studies (Zheng et al., 2018; Kong et al., 2020). This type of rating variation can be assessed at the product level and at the individual review level. At the product level, the variation in average ratings of different dimensions reflects a sort of product quality equilibrium related to product attributes, and we denote this variation as *the product Attribute Dispersion* (*AttriDispersion*). For a certain review, we denote the variation of its multidimensional ratings as *the review's attribute rating differences* (*AttriRatingDiff*) instead.

We take into account three different aspects of how consumers perceive the ranking inconsistency from a multidimensional review: ranking positions of the top- and lowest-rated attributes, as well as the overall ranking order of all attributes. In a differential market, firms typically decide to promote a few "prominent" attributes with highest quality while retaining a relatively lower quality level for other attributes (Zhu and Dukes, 2017; Lauga et al., 2022). Therefore, when a product's best (worst) prominent attribute is not given with the highest (lowest) rating in a multidimensional review, consumers may perceive information inconsistency. We use the terms *RankBest* and *RankWorst* to indicated if the best and worst prominent attributes of a product are ranked correctly in a multidimensional review, respectively. Furthermore, consumers will also perceive an individual ranking order of a product's attributes from a multidimensional review, and by comparing this ranking order with the overall attribute rankings of the product, they will make judgement on whether the individual ranking order is consistent with the overall rankings.

With the abovementioned variables of cross-attribute rating and ranking inconsistency, we develop the following hypotheses.

Cross-Attribute Rating Inconsistency and Review Helpfulness

The cross-reviewer word-of-mouth dispersion referring to the variation of reviewers' ratings to a product plays an important role in consumer behavior studies for traditional SD review systems. Moon et al. (2010) suggested that word-of-mouth dispersion negatively affects consumer satisfaction, But Lee et al. (2021) empirically demonstrated that word-of-mouth dispersion positively affects the helpfulness of reviews. In addition to the cross-reviewer rating variation, consumers can also observe the rating variation across different dimensions in the multidimensional rating context. According to Kwark et al. (2014), consumers decide to choose a product when the product's quality on each attribute satisfies their preference heterogeneity. It is difficult for firms to provide "perfect" products that are with greatest quality at all attributes, so instead, they typically only promote one or a few "prominent" attributes to cater specific market segments (Lauga et al., 2022; Zheng et al., 2022). Multidimensional ratings can then be seen as consumer word-of-mouth regarding the quality distribution of a product. Focusing on the impact of cross-attribute rating inconsistency on review helpfulness, consumers may find it difficult to identify the product attributes that are most important to their decisions if the multidimensional ratings are highly inconsistent (Liu and Karahanna, 2017). As a result, they are more likely to check the reviews to reduce perceived uncertainty about the product according to information diagnosticity theory. For example, Qiu et al. (2012) argued that a zero variance between dimensional ratings makes consumers doubt the credibility of online product reviews and tend to reject them. Zheng et al. (2018) showed that moderate cross-dimensional rating variation can effectively improve the credibility of online reviews and enhance product sales.

In this study, we take into account cross-attribute rating inconsistency both at a product level and a single review: we call the variation of the average ratings of a product across different dimensions as the product attribute dispersion (*AttriDispersion*); and we call the variation of a single reviewer's multidimensional ratings as its attribute rating difference (*AttriRatingDiff*). The metric of standard deviation is used to measure the both types of cross-attribute rating inconsistency and we propose the following hypothesis based on the above discussions.

H1a: In the multidimensional rating context, the product cross-attribute dispersion negatively impacts review helpfulness.

H1b: In the multidimensional rating context, the review cross-attribute rating differences positively impacts its helpfulness.

Attribute Ranking (In)consistency and Review Helpfulness

The information of reviewer rankings on product attributes has not been investigated before. Besides the rating value of each dimension, consumers can also observe the ranking order on product attributes from a multidimensional review. From the perspective of consumer rating behavior, consumers are thought to be with heterogenous preferences on product attributes (Liu and Karahanna, 2017), and they can more easily determine which attributes of a product are more or less prominent rather than give each attribute a certain rating value. For a specific product, the overall ranking order of its attributes reveals which attributes are the most and the worst prominent, and this reflects the firm's differential quality strategies (Zhu and Dukes, 2017; Lauga et al., 2022). For a single multidimensional review, other consumers observe inconsistent rankings if the attribute ranking order implied from this review differs from the product's overall attribute rankings, such as the prominent attributes are not ranked at the top or two attributes are ranked reversely. Not like the abovementioned attribute rating inconsistency that refers to the difference between dimension ratings, the proposed attribute ranking inconsistency reflects the difference between an individual review and the overall reviews of a product. According to the information attribution theory (Sen and Lerman, 2007), people tend to attribute an individual's behaviors that are consistent with the group to internal factors (e.g., product quality) and attribute the behaviors that are inconsistent with group to external factors (e.g., reviewer or context reasons). Further, Qiu et al. (2012) demonstrated that consumers perceive a review as credible and helpful if they attribute the review more to the internal factors of product quality and less to the external factors of reviewer or context. Thus, we argue that the overall attribute ranking order of a product reflects its internal quality, and when reading a single review with consistent rankings, consumers tend to make internal attributions and regard it as credible and helpful. Inversely, when reading a review with obviously inconsistent rankings on the product attributes, consumers are more likely to attribute the review to non-product factors such as reviewer providing false information due to monetary rewards, and this results in a negative perception of the review helpfulness.

In this study, we propose three types of ranking inconsistency information in multidimensional reviews: RankBest, RankWorst, and RankNDCG. RankBest and RankWorst are dummy variables denoting whether the best and the worst product attributes (as determined by the product's average ratings are ranked) are correctly ranked in a single review. We import the metric of NDCG (Normalized Discounted Cumulative Gain, Järvelin and Kekäläinen, 2002) to measure the ranking consistency degree between the ranking order in a single review and the overall ranking order of a product, named as RankNDCG. To make it comparable for different reviews, we only consider the attribute ranking positions in a single review, omit its attribute rating scores, and use the product overall rankings as the baseline. In detail, assume that $[a_1, a_2, \ldots, a_K]$ are attributes sorted in descending order according to the average attribute ratings of a product, and rel_i is the average rating (relevance) of the ***i***-th attribute, then given a specific multidimensional review, we denote p_i as the position for attribute a_i in the single review's descending ranking order, and the DCG (Discounted Cumulative Gain) of the review's rankings is defined as:

$$DCG = \sum_{i=1}^{K} \frac{rel_i}{\log_2(p_i + 1)}$$

The RankNDCG is then calculated as the DCG score of a single review's ranking divided by the ideal (maximum) DCG score, which is the DCG of the baseline ranking, i.e., the product overall attribute ranking.

Notice that the higher the above variables are, the more consistent is the ranking information of a review, so we use ranking consistency instead of ranking inconsistency in the following hypothesis:

H2: In the multidimensional rating context, the attribute ranking consistency in terms of RankNDCG (**H2a**), RankBest (**H2b**) and RankWorst (**H2c**) positively impacts review helpfulness.

Moderating Effect of Product Type

Literature reveals that product types in terms of premium and ordinary types will moderate the impact of information inconsistency on perceived review helpfulness. Kong et al. (2020) found that ordinary products raise consumers' perceptions of risk and uncertainty compared to premium products in the automobile market. In specific markets like cars, brand information can be adopted as a simple resource to evaluate if a product is premium (luxury brand) or ordinary (non-luxury brand). According to information signal theories, brand information provides consumers with signals about the condition and quality of products (Ko et al., 2019). In other words, consumers use brands as a signal to reduce perceived risk and uncertainty about product quality. Therefore, we consider a product is premium if it is with a luxury brand and explore the moderate effects of brand information on the relationships between cross-attribute inconsistency and multidimensional review helpfulness. From the perspective of information diagnosticity (Li, 2018), consumers tend to seek more diagnostic information when faced with difficult or ambiguous judgments.

As for cross-attribute rating information, we follow previous study that a high variation of attribute ratings leads to greater product uncertainty and that consumer's perception of uncertainty from the cross-attribute rating inconsistency varies for luxury and non-luxury products. First, for the product-level attribute rating inconsistency, as named as product attribute dispersion in our study, it has been discussed in hypothesis h1a that the product attribute dispersion generally negatively impacts the review helpfulness. However, consider that luxury products typically satisfy consumer personalized preferences and high product attribute dispersion may lead to high quality in differential markets. For example, a luxury sports car model may attract people by its excellent force power, even though it is "space" or "fuel consumption" attributes are worse than other cars. Hence, we expect that the negative impact of product level attribute dispersion on review helpfulness will be weakened or even reversed to be positive for luxury (premium) products. The same, for the individual review-level attribute rating difference, we predict it will positively impact review helpfulness as in the hypothesis H1b, and this impact will be weakened for luxury (premium) products, for which consumer might perceive lower risks and uncertainty. We propose the following hypotheses.

H3a: The product attribute dispersion is less negatively related to review helpfulness for luxury products than for non-luxury products.

H3b: The attribute rating differences is less positively related to review helpfulness for luxury products than for non-luxury products.

Luxury brand products are often associated with higher prices and quality due to greater investments in product design and inspection, which increase the reliability of product quality (Luo and Sun, 2016). Beverland (2004) highlighted that consumers tend to focus more on the overall quality for luxury products than for non-luxury products. When the attribute ranking in an individual review aligns with the overall attribute ranking order of a product, it indicates that the reviewer's opinion about the product's quality is consistent with that of other consumers, and this will increase other consumers' trust on this single review. It can be presumed that for luxury brand products, consumers are more concerned about whether individual reviews are consistent with the overall attribute ranking. Therefore, the positive effect of the overall attribute ranking difference on review helpfulness is more significant among luxury (premium) products. Conversely, for ordinary products, consumers often have high uncertainty and do not trust their quality directly because of the low price and quality (Kong et al., 2020). As a result, consumers look for more diagnostic information. Zheng et al. (2018) found that extreme cues are less ambiguous and more diagnostic than moderate intensity cues. We believe that the ranking positions of the product's best and worst prominent attributes can serve as extreme cues and influence consumer perceptions. Therefore, it can be expected that the positive effect of the ranking positions of the product's best and worst prominent attributes on review helpfulness would be stronger in non-luxury products. Based on the above analysis, we propose the following hypotheses.

H4a: The overall attribute ranking consistency (RankNDCG) is more positively related to review helpfulness for luxury products than for non-luxury products.

H4b: The ranking consistency the product's best prominent attribute (RankBest) is more positively related to review helpfulness for non-luxury products than for luxury products.

H4c: The ranking consistency the product's worst prominent attribute (RankWorst) is more positively related to review helpfulness for non-luxury products than for luxury products.

Empirical Analysis on Car Market

Data Collection

We collect car market multidimensional reviews from Edmunds website (https://www.edmunds.com/), which is a leading online platform for car ratings. Automotive products are chosen for empirical analysis because consumers usually invest time and effort in reading reviews on each dimension of car products before making decisions. The car market is a high-differential market where firms are with their own prominent attributes, such as space, fuel consumption, interior, etc. Buying a car is also considered as with high risks and uncertainties (Dimoka et al, 2012), which make it difficult for consumers to make quick decisions without word-of-mouth information. In Edmunds, consumers give multidimensional ratings on a scale of 1 to 5 stars, and there are 7 rating dimensions: *Safety*, *Technology*, *Performance*, *Interior*, *Comfort*, *Reliability* and *Value*, considered as the attributes of a car product. Figure 2 shows an example online review with multidimensional ratings in Edmunds, and we make notations on what information would be observed by readers.

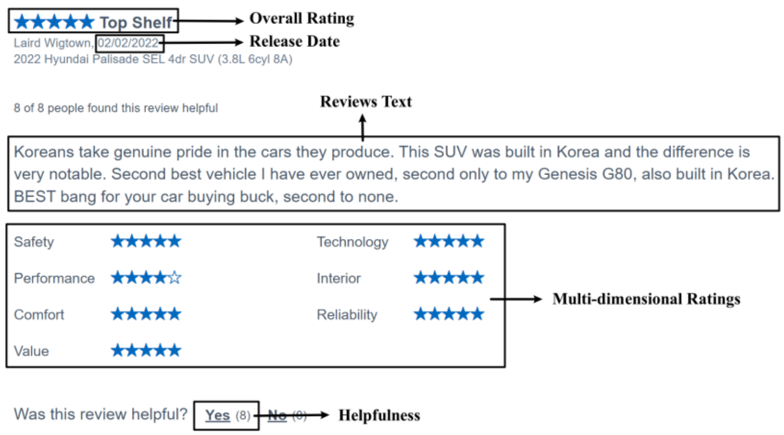

Figure 2. Multidimensional Review on Edmunds.com

According to the settings of Edmunds, a car product refers to a car model of a brand in a specific year, such as the "BMW 3 series 2022" or "Audi A6 2022". We collected the multidimensional reviews of all car models in the US and Europe markets in 2022 from Edmunds.com using a Python crawler program. Car models with fewer than 10 reviews and those with overall ratings higher than 4.95 stars are excluded from the data to ensure the statistical significance of each metric. Finally, the data contains 8281 consumer multidimensional reviews for 226 car models.

Variable Measurement

The dependent variable in this study is review helpfulness, measured by the cumulative number of the "helpful" votes for a single multidimensional review, denoted as *Helpfulness*.

As shown in Figure 1, independent variables considered in this study are measured as follows. *AttriDispersion* is measured as the standard deviation of a product's average ratings on all dimensions, and *AttriRatingDiff* is measured as the standard deviation of the 7-dimension ratings in a single review. As abovementioned, *RankNDCG* is measured as the NDCG score of the attribute ranking order in a single review compared to the overall attribute ranking order of a car model. RankBest (vs. RankWorst) is a dummy variable, which is 1 if the highest (vs. lowest) rated attribute of a car model is also with the highest (vs. lowest) rating in a single review, and 0 otherwise.

Various control variables are included according to a comprehensive survey of existing studies of online review helpfulness. Variables at the product level include product valence (Zhou and Guo, 2017; Yin et al., 2016; Kong et al., 2020), review volume (Choi and Leon, 2020), cross-reviewer rating dispersion (Lee et al., 2021). Variables at the review level include the overall rating (Kong et al., 2020), rating extremity (Filieri et al., 2018), rating inconsistency (Yin et al., 2016), review length (Mudambi and Schuff, 2010; Siering et al., 2018), review date (Choi and Leon, 2020).

As aforementioned, we adopt brand information to specify if a car is premium or ordinary product and import it as a moderating variable in our study. In Edmunds website, cars are explicitly marked if they are luxury or non-luxury products. According to the settings in Edmunds, luxury car brands in our dataset include: Acura, Alfa-Romeo, Audi, BMW, Cadillac, Genesis, Infiniti, Jaguar, Jeep, Land, Lexus, Lincoln, Maserati, Mercedes-Benz, Mini, Porsche, Tesla, Volvo. We name the moderating variable as *Luxury*, and set it as 1 if a car product is with a luxury brand.

The definitions of all variables are summarized in Table 1.

Variable	Definition
Dependent Variable	
$Helpfulness_j$	Cumulative number of helpfulness votes for review *j*
Independent Variables: Attribute Rating Inconsistency	
$AttriDispersion_p$	Standard deviation of the average ratings on all 7 dimensions of the reviewed car model *p*
$AttriRatingDiff_j$	Standard deviation of the 7-dimension ratings in review *j*
Independent Variables: Attribute Ranking Consistency	
$RankNDCG_j$	NDCG score of the attribute ranking order in review *j* compared to the overall attribute ranking order of the reviewed car model
$RankBest_j$	1 if the top-rated attribute of review *j* is also the top-rated attribute of the reviewed car model, otherwise 0
$RankWorst_j$	1 if the lowest-rated attribute of review *j* is also the lowest-rated attribute of the reviewed car model, otherwise 0
Control Variables: Product Characteristics	
$Valence_p$	Mean value of the overall rating of the reviewed car model *p*
$Volume_p$	Total number of reviews of the reviewed car model *p*
$CrowdDispersion_p$	Standard deviation of the overall ratings of all reviewers for the reviewed car model *p*
Control Variables: Review Characteristics	
$OverallRating_j$	Overall rating of review *j*, (1-5)
$OverallRatInc_j$	Difference between the overall rating of review *j* and the reviewed car model's average (overall) rating
$ExtremeRating_j$	1 if the overall rating of review *j* is 1 or 5, otherwise 0
$WordCount_j$	The number of words in the review text of review *j*
$ReviewDate_j$	The number of days between the published date and the crawled date of review *j*

Table 1. Variable definitions

Preliminary Statistical Analysis

Descriptive statistics for the main variables are summarized in Table 2. The average value of review helpfulness votes is 10.32, and its standard deviation is 17.24. This indicates that the dependent variable in the sample data is highly discrete. It can be found that the reviews on Edmunds' platform are mostly positive, with its overall rating have an average value of 4.09. On average, a car product (model) receives 49 reviews. The correlations between the main variables are summarized in Table 3, which shows that the dependent variable review helpfulness is significantly correlated with most of the independent and control variables. To address the concern of multicollinearity in the model, we conducted a VIF test for both the independent and control variables. The results, as shown in Table 4, indicate that all variables in the model have VIF values below 10, indicating that there is no significant multicollinearity problem.

Variable	Mean	SD	Min	Max
Helpfulness	10.32	17.24	0	342
AttriDispersion	0.23	0.12	0.06	0.85
AttriRatingDiff	0.51	0.49	0	2.14
RankNDCG	0.98	0.02	0.88	1
RankBest	0.87	0.34	0	1
RankWorst	0.71	0.46	0	1
Valence	4.04	0.50	2.32	4.90
Volume	49	26	10	134
CrowdDispersion	1.31	0.30	0.31	1.94
OverallRat	4.09	1.39	1	5
OverallRatInc	1.05	0.76	0	3.67
WordCount	692	833	1	7543
ReviewDate	582	410	21	2863

Table 2. Descriptive Statistics

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.Helpfulness	1.00													
2.AttriDispersion	0.02	1.00												
3.AttriRatingDiff	0.11	0.29	1.00											
4.RankNDCG	0.06	-0.49	0.31	1.00										
5. RankBest	-0.02	-0.04	-0.30	-0.01	1.00									
6. RankWorst	-0.01	0.03	-0.29	0.02	0.15	1.00								
7.Valence	-0.06	-0.73	-0.28	0.46	0.12	0.02	1.00							
8.Volume	0.09	0.14	0.09	-0.14	-0.06	-0.04	-0.34	1.00						
9.CrowdDispersion	0.06	0.51	0.21	-0.40	-0.11	-0.02	-0.83	0.27	1.00					
10.OverallRat	-0.11	-0.28	-0.72	-0.22	0.31	0.11	0.36	-0.13	-0.30	1.00				
11.OverallRatInc	0.08	0.27	0.42	-0.13	-0.17	-0.04	-0.41	0.14	0.44	-0.68	1.00			
12.ExtremeRating	-0.03	-0.06	-0.41	-0.18	0.23	0.20	0.11	-0.05	-0.06	0.38	0.13	1.00		
13.WordCount	0.28	0.08	0.19	0.05	-0.08	-0.07	-0.07	0.00	0.04	-0.14	0.04	-0.16	1.00	
14.ReviewDate	0.28	-0.03	-0.05	0.00	0.01	0.02	0.09	-0.16	-0.11	0.07	-0.08	0.02	0.08	1.00

Table 3. Correlation Analysis

Variable	VIF	Variable	VIF
AttriDispersion	3.189	Volume	1.191
AttriRatingDiff	3.096	CrowdDispersion	3.752
RankNDCG	2.712	OverallRat	5.281
RankBest	1.182	OverallRatInc	3.919
RankWorst	1.230	WordCount	1.055
Valence	6.173	ReviewDate	1.042

Table 4. Multicollinearity test

Empirical Results

As shown in Figure 1, the main effects in our model are the impact of attribute rating and ranking information on the review helpfulness. The dependent variable is *Helpfulness*. The independent variables are *AttriDispersion*, *AttriRatingDiff*, *RankNDCG*, *RankBest*, and *RankWorst*. With variables of both product and review characteristics, we propose a regression model as follows.

$$\begin{aligned} Helpfulness_j = {} & b_0 + b_1 AttriDispersion_p + b_2 AttriRatingDiff_j + b_3 RankNDCG_j \\ & + b_4 RankBest_j + b_5 RankWorst_j + b_6 Valence_p + b_7 Volume_p \\ & + b_8 CrowdDispersion_p + b_9 RatingInconsist_j + b_{10} OverallRating_j \\ & + b_{11} ExtremeRating_j + b_{12} WordCount_j + b_{13} ReviewDate_j + e \end{aligned} \tag{1}$$

The sample size of the data is 8281 and empirical results of our model are collected in Table 5.

For the attribute rating inconsistency information, the product cross-attribute dispersion is found to have a significant negative impact on the review helpfulness (AttriDispersion, b=-0.054, p=0.002), whereas the positive impact of the review's cross-attribute rating difference is not significant (AttriRatingDiff, b=0.031, p=0. 082). Therefore, the hypotheses H1a is supported while H1b is not. The lack of support for H1b could be attributed to the varying requirements and expectations among consumers regarding the usefulness of reviews. It is likely that different consumers prioritize and have different preferences when reviewing products. In this regard, most consumers are more inclined to prioritize the overall performance and overall rating of a product, rather than paying close attention to the differences in attribute ratings within individual reviews.

For the attribute ranking (in)consistency information, the overall ranking consistency (RankNDCG, b=0.049, p=0.003) and the ranking consistency of the product's best prominent attribute (RankBest, b=0.028, p=0.011) are found with significant positive relations to review helpfulness, whereas the ranking consistency of the product's worst prominent attribute (RankWorst, b=0.015, p=0.181) has no significant impact. It appears that consumers put more weight on the ranking position of the best attribute of a product than that of the worst one when reading a multidimensional review. These results support the hypothesis H2a and H2b, but not support the H2c.

Dependent Variable: *Helpfulness*		
	B	**P-value**
Main Effects: Attribute Rating Inconsistency		
AttriDispersion	-0.054**	0.002
AttriRatingDiff	0.031	0.082
Main Effects: Attribute Ranking Consistency		
RankNDCG	0.049**	0.003
RankBest	0.028*	0.011
RankWorst	0.015	0.181
Controls: Product Characteristics		
Valence	-0.014	0.559
Volume	0.126***	0.000
CrowdDispersion	0.063***	0.001
Controls: Review Characteristics		
OverallRat	-0.074***	0.001
OverallRatInc	-0.007	0.718
ExtremeRating	0.056***	0.000
WordCount	0.250***	0.000
ReviewDate	0.292***	0.000
Number of obs.	8281	
F	137.879***	
Adjusted R^2	0.177	
$p < 0.05$*, $p < 0.01$**, $p < 0.001$***		

Table 5. Estimation Results

Group regressions are conducted to verify the moderating effects of luxury and non-luxury brands. The results are collected as in Table 6.

Regarding the effects of cross-attribute rating inconsistency, the hypotheses H3a and H3b are supported. AttriDispersion is found to have significant negative influence on review helpfulness for non-luxury products (b=-0.055, p=0.007), but this effect turns to be positive for luxury products (b=0.083, p=0.008). This demonstrates that the negative impact of the product cross-attribute dispersion on review helpfulness is weakened and even reversed by the moderating effect of the product type (luxury or premium). We also find that AttriRatingDiff has a significant positive relationship with review helpfulness only for non-luxury products (b=0.051, p=0.020). It also reports that the effect of AttriRatingDiff on helpfulness is significant in the non-luxury brand subgroup, although H1b is not supported by the whole data.

The hypotheses H4a-H4b regarding the effects of cross-attribute ranking (in)consistency information are all supported. For luxury brands, RankNDCG has a significant and positive impact on review helpfulness (b=0.072, p=0.006), whereas RankBest (b=-0.004, p=0.792) and RankWorst (b=-0.016, p=0.355) have no significant effects. For non-luxury brands, however, RankBest (b=0.044, p=0.002) and RankWorst (b=0.031, p=0.026) positively affect review helpfulness while RankNDCG (b=0.019, p=0.361) does not. This demonstrates that product type in terms of luxury or non-luxury brands indeed moderates the influence of cross-attribute ranking information on consumers' perception on the value of a multidimensional review. It is also noteworthy that H2c is not supported by the whole data but H4c is supported in the non-luxury subsample.

DV: *Helpfulness*	**Luxury brand**		**Non-luxury brand**	
	B	**P-value**	**B**	**P-value**
Main Effects: Attribute Rating Inconsistency				
AttriDispersion	0.083**	0.008	-0.055**	0.007
AttriRatingDiff	0.005	0.864	0.051*	0.020
Main Effects: Attribute Ranking Consistency				
RankNDCG	0.072**	0.006	0.019	0.361
RankBest	-0.004	0.792	0.044**	0.002
RankWorst	-0.016	0.355	0.031*	0.026
Controls: Product Characteristics				
Valence	0.111**	0.008	-0.022	0.480
Volume	0.044*	0.014	0.125***	0.000
CrowdDispersion	0.167***	0.000	0.021	0.425
Controls: Review Characteristics				
OverallRat	-0.055	0.107	-0.117***	0.000
OverallRatInc	0.052	0.070	-0.059*	0.028
ExtremeRating	0.031	0.136	0.083***	0.000
WordCount	0.276***	0.000	0.242***	0.000
ReviewDate	0.341***	0.000	0.306***	0.000
Number of obs.	3206		5075	
F	75.838***		88.713***	
Adjusted R^2	0.233		0.183	
$p < 0.05$*, $p < 0.01$**, $p < 0.001$***				

Table 6. Group regression results (luxury vs. non-luxury products)

Robustness Check

Consider that the numbers of luxury and non-luxury products are not balanced in our data, we conduct an additional analysis to ensure the robustness of our findings. In the original dataset, reviews of luxury brand products account for 38.72% (3206) of the total reviews, whereas non-luxury brand products account for 61.28% (5075). To investigate whether the unbalanced sample sizes affect our study's results, we remove the brand Alfa Romeo with the lowest numbers of reviews for luxury product group, and remove the brand Toyota with the highest numbers of reviews for luxury product group, respectively (Wang et al., 2021). In the new dataset, the number of reviews for luxury brand products is 3149, accounting for 42.29% of all reviews, while the number of reviews for non-luxury brand products is 4298, accounting for 57.71% of all reviews. The group regression results of the new dataset are in Table 7, and it shows that the conclusions are fully consistent with the results of the original data. It can be concluded that our conclusions remain robust for different datasets.

DV: *Helpfulness*	**All products**		**Luxury brand**		**Non-luxury brand**	
	B	**P-value**	**B**	**P-value**	**B**	**P-value**
Main Effects: Attribute Rating Inconsistency						
AttriDispersion	-0.062***	0.001	0.079*	0.014	-0.068**	0.002
AttriRatingDiff	0.034	0.062	0.005	0.867	0.058*	0.013
Main Effects: Attribute Ranking Consistency						
RankNDCG	0.050**	0.003	0.071**	0.007	0.018	0.441
RankBest	0.028*	0.014	-0.005	0.779	0.048***	0.001
RankWorst	0.019	0.092	-0.016	0.346	0.041**	0.007
Controls: Product Characteristics						
Valence	-0.028	0.275	0.108**	0.010	-0.036	0.273
Volume	0.101***	0.000	0.044*	0.016	0.105***	0.000
CrowdDispersion	0.076***	0.000	0.167***	0.000	0.030	0.282
Controls: Review Characteristics						
OverallRat	-0.087***	0.000	-0.054	0.112	-0.141***	0.000
OverallRatInc	-0.013	0.535	0.055	0.054	-0.078**	0.007
ExtremeRating	0.063***	0.000	0.027	0.190	0.098***	0.000
WordCount	0.255***	0.000	0.339***	0.000	0.245***	0.000
ReviewDate	0.307***	0.000	0.279***	0.000	0.324***	0.000
Number of obs.	7447		3149		4298	
F	135.262***		74.804***		83.326***	
Adjusted R^2	0.190		0.234		0.199	
$p < 0.05^*$, $p < 0.01^{**}$, $p < 0.001^{***}$						

Table 7. Robustness Check Group Regression Results

Discussions

Key Findings

Our empirical results based on the review data of a real car review website show that most of our hypotheses are supported. The following key findings of our research are summarized. (a) Both cross-attribute rating and ranking inconsistency will significantly impact the helpfulness of a multidimensional review. In detail, the product cross-attribute dispersion has a significant negative impact on review helpfulness, while the overall attribute ranking consistency and the ranking position of the product's best prominent attribute positively impact review helpfulness. (b) Luxury and non-luxury product types adjust the impact of cross-attribute rating inconsistency on review helpfulness. In detail, the product cross-attribute dispersion negatively impacts the review helpfulness for non-luxury products but it positively impacts that for luxury products, while the cross-attribute rating difference of a single review positively impacts it helpfulness only if the product is non-luxury. (c) Luxury and non-luxury product types also adjust the impact of cross-attribute ranking inconsistency on review helpfulness. In detail, the overall attribute ranking consistency significantly impacts the review helpfulness only for luxury products, while the ranking consistency of the product's best and worst prominent attributes impact the review helpfulness only for non-luxury products.

Theoretical and Management Implications

Our findings offer several important theoretical implications. First, we propose new impact metrics for online review helpfulness from the perspectives of cross-attribute rating and ranking of multidimensional reviews. Second, we extend previous studies that have focused primarily on the rating inconsistency and demonstrate that attribute ranking inconsistency is also a valuable source of information inconsistency and it also plays an important role in affecting consumer behaviors. Finally, existing literature lacks a comprehensive theoretical model regarding the helpfulness of multidimensional reviews. This study fills this gap by providing a systematic theoretical model of the factors that influence the helpfulness of multidimensional reviews. From the perspective of information diagnosis and attribution, this study not only enhances our understanding of the consumer's review information processing process but also expands the existing theoretical framework surrounding the helpfulness of multidimensional reviews.

This study also has managerial implications for online review platforms and manufacturers. For online review platforms, they can enhance their product review systems by incorporating the dispersion of product attributes on the first page of reviews. This feature would distinguish their platform from others, attracting more consumers. Additionally, a visual indicator can be utilized beneath individual reviews to denote the ranking position of the product's best prominent attribute (e.g., using green to indicate consistency and red to indicate inconsistency). This visual representation enables consumers to better perceive product quality and the helpfulness of reviews. For manufacturers, it is crucial to acknowledge that consumers' perception of attribute ranking consistency may differ depending on the product type. Hence, companies can formulate distinct quality testing strategies based on their brand classifications. Specifically, for luxury brands, greater attention should be given to online reviews displaying higher overall attribute ranking consistency. Conversely, for general brands, emphasis should be placed on online reviews consistently highlighting both the best and worst attributes. These reviews are highly valued by consumers, and companies can leverage them to identify product flaws and improve overall product quality.

Conclusions

In this study, we investigated the cross-attribute rating and ranking inconsistency in multidimensional systems and their impact on review helpfulness. We proposed new impact metrics for multidimensional review helpfulness, such as attribute dispersion, attribute rating differences, and attribute ranking consistency, and verified through empirical analysis that these factors have significant impacts on review helpfulness. This study firstly investigates the attribute ranking information in multidimensional rating systems, and finds that both cross-attribute rating and ranking inconsistency will significantly impact the helpfulness of a multidimensional review. These impacts are also moderated by product types in terms of luxury and non-luxury brands. The product cross-attribute dispersion negatively impacts the review helpfulness for non-luxury products but it positively impacts that for luxury products, while the cross-attribute rating difference of a single review positively impacts it helpfulness only if the product is non-luxury. From the perspective of attribute ranking information, the overall attribute ranking consistency significantly impacts the review helpfulness only for luxury products, while the ranking consistency of the product's best and worst prominent attributes impact the review helpfulness only for non-luxury products. This study also provides insights into the management practices of e-commerce companies. Nevertheless, there are some limitations in our research. In this study, the characteristics of the data may result in endogeneity and generalizability problems. Future research will draw on more data from different markets to investigate the impact of ranking inconsistency on review helpfulness in MD systems. Furthermore, there may be other control variables not included in this study, such as the sentiment of the review text and the nature of the review. Future studies may investigate the relationships between these factors and the proposed cross-attribute ranking inconsistency information.

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