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RESEARCH NOTE

DIFFERENTIAL EFFECTS OF MULTIDIMENSIONAL REVIEW EVALUATIONS ON PRODUCT SALES FOR MAINSTREAM VS. NICHE PRODUCTS[1]

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Despite a large body of literature on online reviews, none have considered the nuanced impacts of how multidimensional reviews affect product sales differently for mainstream vs. niche products. This study seeks to fill this knowledge gap by conducting complementary studies in two product categories (i.e., automobiles and laptops) with different methods (a field study and three lab experiments). Our paper reveals three key insights into the emerging literature and phenomenon on multidimensional review systems: (1) the interdimensional rating variance is more negatively related to product sales for mainstream products than for niche products in the same category, (2) the intradimensional rating valence on the dominant dimension of a product is more positively related to product sales for niche products than for mainstream products, and (3) the intradimensional rating variance on the dominant dimension of a product is more negatively related to product sales for niche products than for mainstream products. Our research provides important managerial implications for both product providers and review platforms.

Keywords: Online reviews, multidimensional ratings, product sales, mainstream product, niche product, dominant dimension

Introduction

Product variety and complexity both increase as the economy grows (Schwartz, 2004). To evaluate products that differ on multiple attributes or dimensions, consumers commonly engage in extensive information search (Levy et al., 2013), particularly for high-involvement products such as electronics, appliances, and automobiles (Gu et al., 2012; Laurent & Kapferer, 1985). To help consumers make better purchase decisions, many online review platforms have

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started to implement multidimensional rating systems (Chen et al., 2018; Liu & Karahanna, 2017; Schneider et al., 2021) wherein a user provides ratings and textual comments on multiple product dimensions. For example, cars.com allows consumers to rate automobiles on performance, comfort, exterior styling, interior design, value for the money, and reliability, while CNET allows consumers to rate cameras on design, features, performance, and image quality. Despite the increasing prevalence of multidimensional reviews in practice, their nuanced effects on product sales have not been systematically studied.

Compared with aggregate reviews, multidimensional reviews contain more abundant and detailed information that goes beyond an overall valence (e.g., Chen et al., 2011; Chevalier & Mayzlin, 2006), volume (e.g., Duan et al., 2008; Liu, 2006), and variance (e.g., Clemons et al., 2006; Sun, 2012), and may affect consumers' product choices in a more nuanced way. To illustrate, consider three products with the following average ratings on four product dimensions measured on a 10-point scale: A (9, 5, 5, 5), B (6, 6, 6, 6), and C (5, 5, 5, 9). Although all products have the same overall rating of 6, they differ substantially in how the ratings vary across the four dimensions. A low interdimensional rating variance (e.g., Product B) indicates that the reviewed product has a relatively balanced performance across dimensions, whereas a high interdimensional rating variance (e.g., Product A or C) indicates that dimensional ratings are distributed unevenly. As such, we cannot simply view Products A (9, 5, 5, 5) and C (5, 5, 5, 9) as the same without further information to distinguish the four dimensions.

An important contextual factor in examining the nuanced impact of multidimensional reviews is product type—namely, mainstream vs. niche products. Building on Sujan and Bettman (1989), we define a product as a niche (mainstream) product if one dimension, i.e., the dominant dimension, is strongly (not strongly) discrepant from that of others in the general category schema from the firm's perspective. Correspondingly, we draw from the literature on market positioning (e.g., Adner et al., 2014; Palmatier & Sridhar, 2017) and define the dominant dimension for a product as the dimension on which the product is mostly differentiated from others in the general category schema from the firm's perspective. For example, Mini Cooper Hardtop is a niche product because its dominant dimension, i.e., its exterior styling, sets it apart from other passenger cars in the category. In contrast, Toyota Camry is categorized as a mainstream product because fuel efficiency is its dominant dimension but this dimension is not discrepant enough to distinguish it from other cars. The difference between mainstream and niche products is also reflected in the product's distinctive evaluation strategies. Prior research (Sujan & Bettman, 1989) suggests that niche products are likely to be evaluated by consumers under a disjunctive rule (e.g., Dzyabura & Hauser, 2011) and mainstream products are likely to be evaluated under a conjunctive rule (e.g., Gilbride & Allenby, 2004). In other words, consumers of niche products prefer products with extraordinary performance on the dominant dimension, while consumers of mainstream ones like products with performance that lies above a cut-off for all dimensions.

Because of the different evaluation strategies, multidimensional reviews may affect sales for mainstream products and niche products differently. Using the same example above, despite Product A and B having the same average rating of 6 out of 10, Product A has a much higher interdimensional rating variance—namely, the variance of average ratings across dimensions for a product. As consumers of mainstream products are more likely to use a conjunctive decision rule and favor a balanced product with a smaller performance variation across dimensions, we expect that a higher interdimensional rating variance should have an increased negative effect on sales for mainstream products versus those for niche products. Moreover, since consumers focus more on the dominant dimension when evaluating niche products versus mainstream products (Sujan & Bettman, 1989), the effects of intradimensional rating valence and variance on the dominant dimension should matter more for niche products than for mainstream products. Therefore, depending on if the dimension with the highest score is the dominant one or not, respective review scores of 9, 5, 5, 5 and 5, 5, 5, 9 may either help or hurt the sales of niche products. We herein define the rating valence of the dominant dimension as the cross-reviewer average rating for the dominant dimension and the rating variance of the dominant dimension as the cross-reviewer rating variance for the dominant dimension. These concepts measure the performance of one dimension (i.e., intradimension) for a product in consumer reviews instead of that of all dimensions (i.e., interdimension).

Although prior studies on the impact of overall product reviews have considered different product categories (Sun, 2012; Wang et al., 2015; Zhu & Zhang, 2010), none have studied nuanced impacts in the setting of multidimensional rating systems. The objective of this study is to fill this knowledge gap by answering the following two questions. First, how does interdimensional (i.e., cross-dimensions) rating variance affect the sales of niche products differently from mainstream products? Second, how do intradimensional (i.e., cross-reviewers) rating valence and variance on the dominant dimension of a product respectively affect the sales of mainstream products differently from niche products?

To answer the research questions, we adopted a multimethod approach by combing a field study with three lab experiments. We first leveraged a unique proprietary dataset in the automotive industry to generate several interesting correlational findings. Specifically, we obtained multidimensional review information and monthly sales records for 384 cars from January 2015 to September 2016 and performed panel linear regressions. We then conducted three lab experiments in another product category (i.e., laptops) to establish the causal relationships. This multimethod approach enabled us to enhance both the external and internal validity of our findings. The results from the multiple studies collectively reveal that: (1) interdimensional rating variance is more negatively related to product sales for mainstream products than for niche products, (2) intradimensional rating valence on the dominant dimension of a product is more positively related to product sales for niche products than for mainstream products, and (3) intradimensional rating variance on the dominant dimension of a product is more negatively related to product sales for niche products than for mainstream products.

Our paper makes three contributions to the literature on online reviews. First, to the best of our knowledge, this is the first study that decomposes the rating variance into the interdimensional (i.e., cross-dimensions) rating variance and the intradimensional (i.e., cross-reviewers) rating variance and examines their respective effects on sales of mainstream vs. niche products. The interdimensional rating variance captures the discrepancy in performance across dimensions, whereas the intradimensional rating variance of the dominant dimension captures the inconsistency among reviewers on the dominant dimension. Most notably, consumers of niche products are more tolerant of a high interdimensional rating variance, but they prefer products with a low rating variance on the dominant dimension. On the flip side, consumers of mainstream products prefer products with a low interdimensional rating variance. We find that the impact of variance on sales depends on both the variance type and the product type, which offers new insights into the interpretation of the mixed findings on the effects of variance in the overall product rating on product sales (e.g., Chintagunta et al., 2010; Clemons et al., 2006; Moe & Trusov, 2011; Zhu & Zhang, 2010).

Second, the current work extends the emerging research on multidimensional online review systems (Chen et al., 2018; Liu & Karahanna, 2017; Schneider et al., 2021) by revealing the importance of product type (i.e., mainstream vs. niche) in affecting the way that multidimensional product ratings influence sales. Our empirical results demonstrate that consumers of niche products tend to prefer products with better performance (as reflected in both rating and variance) on their dominant dimension, while consumers of mainstream products prefer relatively balanced products with a smaller interdimensional rating variation. The distinctions between mainstream vs. niche products advance our understanding of the nuanced effects of multidimensional online reviews on product sales.

Third, our first study explores the effect of the dominant dimension in multidimensional online review systems. Online review literature has predominantly used an overall-rating metric (e.g., Chevalier & Mayzlin, 2006; Clemons et al., 2006; Moe & Trusov, 2011) and largely overlooked the impact of dimension-level review characteristics and the importance of certain product dimensions. We find that the valence (variance) on the dominant dimension is positively (negatively) associated with product sales for niche products. The findings provide a fresh perspective to future studies exploring the impact of dimension-level review characteristics.

Our research also offers valuable managerial implications for sellers (i.e., product providers) to develop optimal strategies for product positioning, marketing communication, and product quality improvement. We provide actionable insights into online review systems to help platform operators make more informed decisions.

Conceptual Background

Consumer Multidimensional Information Processing for Evaluating Products

The multi-attribute attitude model provides a useful framework to understand how consumers use information on different dimensions to evaluate and select products (Levy et al., 2013). According to this model, consumers view products as a collection of dimensions. Consumers' product evaluations are based on the product's performance in relevant dimensions and the importance of these dimensions to the consumer. As such, consumers' overall evaluations of an alternative are related to the sum of the performance expectations multiplied by the weights of importance (Wilkie & Pessimier, 1973). Therefore, consumer choices are based on selecting the dimensions that yield the highest utility (Edwards & Newman, 1982).

In addition to this general framework, the information processing literature endorses the view of bounded rationality (Simon, 1955) such that consumers typically have limited cognitive capacity (e.g., working memory and computational capabilities) in processing information (Bettman et al., 1998). Therefore, the consumer choice of product evaluation strategy is often guided by the objective of minimizing cognitive effort and achieving a satisfactory level of decision accuracy (Beach & Mitchell, 1978; Payne & Bettman, 2004). When evaluating and choosing products, consumers may select different strategies in different scenarios (Bettman et al., 1998).

Product Type (Mainstream vs. Niche) and Evaluation Strategy

Product type, i.e., mainstream vs. niche products, is an important contextual factor when we consider consumers' evaluation strategies. Building upon Sujan and Bettman (1989), a product is defined as a niche (mainstream) product if the product is strongly (not strongly) discrepant on its dominant dimension from the general product category schema from the firm's perspective.[2] Correspondingly, we define the dominant dimension as the dimension on which the product is mostly differentiated from others in the same product category schema from the firm's perspective. The classification of products as either "mainstream" or "niche" comes from firms' strategies for differentiation. Given the same production cost, it is virtually impossible to produce a product that excels in every single dimension (Palmatier & Sridhar, 2017)—excellent performance on one dimension often comes at the cost of that of others (e.g., the size of a car is usually negatively correlated to its fuel efficiency; Adner et al., 2014). Porter (1996, p. 69) remarks that "trade-offs are essential to strategy. They create the need for choice and purposefully limit what a company offers." Firms need to make trade-offs between producing products that have extraordinary performance on one dimension (i.e., niche products) or relatively balanced performance across dimensions (i.e., mainstream products).

The key criterion that sets niche products apart from mainstream products is how unique the performance of the dominant dimension is. Because the performance discrepancy of the dominant dimension is strong enough to set it apart from the rest of the market, niche products are not perceived as prototypical category members but rather specialized products. This type of product possibly appeals to a focused market segment (Porter, 1998). In contrast, because the discrepancy of the dominant dimension from the general product category schema is not strong, mainstream products are seen as consistent with the category schema and thus substitutable for other products, possibly affording a wider market (Sujan & Bettman, 1989).

For niche products, a strong discrepancy of the dominant dimension from the general category schema results in great correspondence between the importance of the dominant dimension and product evaluation (Sujan & Bettman, 1989). Niche products are more likely to be evaluated by consumers under a disjunctive decision rule (Gilbride & Allenby, 2004), meaning that if the performance of one dimension can give consumers a feeling of excitement, the product will be considered regardless of the performance of the other dimensions (Dzyabura & Hauser, 2011). In short, niche product consumers are more likely to use a dominant-dimension-superiority evaluation strategy.

In contrast, because mainstream products lack a strong discrepancy in the dominant dimension that sets them apart from the general product category schema, they are assimilated into the category schema and their evaluation is likely to be based on product category membership under a conjunctive decision rule (Sujan, 1985; Sujan & Bettman, 1989), which requires that an alternative be acceptable on all relevant attributes (i.e., above a cut-off on all dimensions) for it to be considered (Gilbride & Allenby, 2004). All else being equal, in a multidimensional choice, consumers of mainstream products are more likely to favor a balanced option with intermediate-level performance on all dimensions. This is because intermediate options have relatively smaller disadvantages than extreme options, and the choice of extreme options increases the risk of potentially making a poor decision (Bettman et al., 1998).

Effect of Interdimensional Rating Variance on Product Sales

Interdimensional rating variance exists when some product dimensions are highly rated while others are poorly rated. As mentioned earlier, consumers of mainstream products are more likely to use a conjunctive rule stating that an alternative failure to pass a low threshold value on any dimension will be rejected (Einhorn, 1970; Gilbride & Allenby, 2004). Consumers of niche products, on the other hand, are more likely to use a disjunctive rule (superiority on the dominant dimension; Dzyabura & Hauser, 2011) and place a higher weight on the performance of the product's dominant dimension (Sujan & Bettman, 1989). For mainstream product consumers, interdimensional rating variance is not desirable as it indicates a performance imbalance among different dimensions that forces them to make a trade-off between those dimensions (Khan et al., 2011). All else being equal, an option with relatively more extreme dimensional ratings (i.e., high interdimensional variance) will tend to be viewed as riskier than an otherwise equivalent option with moderate dimensional ratings, which minimizes the risk of making a

[2] We do not define the concept of mainstream versus niche products using market size as market size (i.e., sales volume) is the outcome variable that we try to predict in the paper.

poor choice, i.e., by betting on the wrong dimension (Mourali et al., 2007). Therefore, mainstream product consumers tend to exclude products with high interdimensional variance from further consideration to avoid perceived product uncertainty and consumption risk—i.e., uncertainty in product performance and negative anticipation of consumption consequences (Dimoka et al., 2012; Hong & Pavlou, 2014; Wu & Lee, 2016). Thus, the variance decreases the sales of the focal product. Bearing the above in mind, while product uncertainty (reflected in rating variances) is generally undesirable, we expect a higher interdimensional rating variance to have an increased negative effect on the sales of mainstream products compared to niche products. We hypothesize as follows:

H1: *All else being equal, interdimensional rating variance is more negatively related to product sales for mainstream products than for niche products.*

Effects of Intradimensional Rating Valence on Product Sales

In a multidimensional rating system, previous buyers submit ratings and leave reviews on each product dimension. Intradimensional rating valence refers to the average rating across reviewers for each product dimension. As the niche product is strongly discrepant in the dominant dimension from the general product category schema, consumers of niche products attach greater weight to the dominant dimension than consumers of mainstream products when forming product evaluations. In other words, consumers of niche (vs. mainstream) products have more readily established dimension preferences such that the dominant dimension is perceived to be of primary importance (Sujan & Bettman, 1989). They are thus more likely to use a dominant-dimension-superiority evaluation strategy and favor the option with a superior dominant dimension, expecting to extract high utility from it (Mourali et al., 2007).

Therefore, all else being equal, higher intradimensional rating valence (i.e., average rating valence) on the dominant dimension leads to higher perceived product attractiveness for niche products than for mainstream products. The superiority of the dominant dimension helps consumers of niche products identify products that better fit their preferences. Bearing this in mind, the higher the rating valence on the dominant dimension of the niche product, the less likely the consumer will be to find close substitutes, thus increasing product sales. Therefore, we propose the following:

H2: *All else being equal, the intradimensional rating valence on the dominant dimension of a product is more positively related to product sales for niche products than for mainstream products.*

Effects of Intradimensional Rating Variance on Product Sales

Similar to the intradimensional rating valence discussion, we focus on the dominant dimension for the intradimensional rating variance. The intradimensional rating variance exists when the dominant dimension is rated highly by some consumers but rated poorly by others. Compared with consumers of mainstream products, consumers of niche products consider the dominant dimension to be more important than other dimensions for determining product utility (Sujan & Bettman, 1989). For example, consumers of gaming laptops place a higher weight on clock speed than on other product dimensions, while consumers of graphic design laptops value the screen display more than other dimensions.

The intradimensional rating variance on the dominant dimension captures the extent to which consumer opinions about the dominant dimension are inconsistent. For niche products, all else being equal, the lower the intradimensional rating variance on the dominant dimension, the higher the consensus among reviewers on the dominant dimension will be, which reduces the consumers' uncertainty about the performance of the dominant dimension (Dimoka et al., 2012) or increases the sense of belonging. As a result, lower cross-reviewer variance on the dominant dimension should increase perceived product attractiveness and affect niche product sales more positively than mainstream product sales. Therefore, we propose the following:

H3: *All else being equal, the intradimensional rating variance on the dominant dimension of a product is more negatively related to product sales for niche products than for mainstream products.*

Field Observational Study

Data Description

The purpose of the field study was to establish associational evidence for the hypotheses we proposed with secondary archival data. We focus on automobiles in our field study. Automobiles are high-involvement products and are typically considered an average person's second most expensive purchase. Therefore, consumers usually devote a considerable amount of time and effort to the search process in this context (Dimoka et al., 2012) and often rely on information from online reviews to assist in purchase decisions. For example, according to a report conducted by J. D. Power in 2015, 68% of car buyers in China visited an automobile review platform before making their purchase (J. D. Power, 2015).

We conducted our field study in collaboration with a leading Chinese automobile review platform (see Table A1 in the Appendix) and major manufacturers. The review platform has cooperative relationships with almost all auto manufacturers and about 90% of dealers in China's passenger car market. The platform allows users to read, write, and share product reviews. To facilitate consumers' purchase decisions, at the top of each product webpage, the platform provides a summary of aggregated ratings and volume. In each review, consumers rate the car they bought on seven dimensions: fuel consumption, handling, horsepower, exterior styling, interior design, comfort, and space. They also write textual comments to justify their numerical ratings. In addition, reviewers provide their purchase dates and purchase prices.

We combined our data set from two archival sources. First, we obtained a full history of user reviews on this platform from September 2012 to October 2016. Second, we obtained the monthly sales data on China's passenger car market from January 2015 to September 2016 for each product. We aggregated user reviews by product and by release month and matched them with our sales data. The unit of analysis in our study was *brand model-month*, which refers to a series of car models from the same brand (e.g., BMW 5 Series) for each month. We classified two products as the same if they had the same manufacturer and brand model name.[3] Products that exited the market during the focal period were excluded from the sample (less than 5%). We also removed products with an average monthly sales volume of 100 or less to exclude anomalous outliers (we conducted robustness checks to change this threshold to 50 or 25). Our final sample contained 7,272 observations for 384 products for up to 21 months.

Measures and Descriptive Statistics

Dominant dimension and product type: We defined a product's dominant dimension as the dimension on which the product is most differentiated from others in the general category schema from the firm's perspective. We conceptualized the dominant dimension for the product as one of the seven key dimensions provided by the platform, i.e., fuel consumption, handling, horsepower, exterior styling, interior design, comfort, and space. We defined products as niche (mainstream) if the product was strongly (not strongly) discrepant on its dominant dimension from the general product category schema—i.e., the passenger cars in the field study from the firm's perspective. Based on these definitions, five industry experts who were blind to the purpose of the study independently labeled the products in the archival data. We first explained the definition of the dominant dimension and mainstream vs. niche products to the experts and then engaged in a training session with two test case examples outside of the sample. The selection criterion for niche products was based on whether the industry experts thought the performance on the dominant dimension was strongly discrepant from that of other passenger cars in China. After ensuring that the experts fully understood the labeling rules, they coded the sampled products based on their own judgments.

The labeling results among the experts were highly consistent. The Fleiss' kappa, which measures interrater reliability, was 0.835 for mainstream vs. niche products and 0.833 for the dominant dimension, indicating agreement among the coders. Fleiss' kappa values were between 0 and 1, with higher values indicating greater consistency among experts. For example, experts agreed that fuel efficiency was the dominant dimension of the Toyota Prius, and exterior design was the dominant dimension of the Mini Cooper. Of a total of 405 products, 62.96% were labeled as niche products, consisting of 33.12% of the total market share. For example, experts viewed the Volkswagen Beetle as a niche product and the Honda Civic as a mainstream one. We list some examples in Table 1.

Dependent variable and independent variables: We used *LogSales* as the dependent variable (i.e., product sales), which is the logarithm-transformed monthly sales volume of a product. We included three key independent variables in our models. First, we measured the interdimensional rating variance (*InterVar*) using the standard deviation of average user ratings among the different dimensions. Second, we measured the intradimensional rating valence (*DominantDimValence*) using the average rating on the dominant dimension of a product. Third, we measured the intradimensional rating variance (*DominantDimVar*) using the standard deviation of ratings among reviewers on the dominant dimension of a product.

Control variables: We controlled for the overall valence and volume for each product in each period, all of which were predictors of sales volume (e.g., Duan et al., 2008; Gu et al., 2012). We defined the overall valence of a product for a given month as the mean of all users' overall ratings up to the last day of that month. We measured review volume for a given month as the cumulative number of reviews up to the last day of that month. To account for the price effect, we included the logarithm of the average reported transaction price (*LogPrice*) of a product in each month as a control variable.

[3] For example, the 2021 Camry is the newer model of the 2020 Camry, and we classified the two products as the same in our sample. Less than 10% of the total products fell under this case.

Table 1. Examples of Dominant Dimension and Mainstream versus Niche Products

Model	Dominant dimension	Mainstream versus niche
Honda Civic	Fuel consumption	Mainstream
Honda CRV	Space	Mainstream
Mazda CX5	Handling	Mainstream
Toyota Camry	Fuel consumption	Mainstream
Volkswagen Lavida	Exterior design	Mainstream
Volkswagen Beetle	Exterior design	Niche
Buick GL8	Space	Niche
Mini Cooper	Exterior design	Niche
Toyota Prius	Fuel consumption	Niche
Volkswagen Golf GTI	Horsepower	Niche

Descriptive statistics: Table B1 in the Appendix reports the summary statistics of the key variables. We report the correlation matrix in Table B2 in the Appendix. To check for potential multicollinearity, we examined the variance inflation factor (VIF) and found that the VIF values are all below the threshold of 10, alleviating this concern.

Model Specification

We estimated the results using panel data linear regression models with two fixed effects, i.e., product fixed effects and time fixed effects. We specified three models as follows. In Model 1, we included the *InterVar* and other control variables. In Model 2, we added *DominantDimValence* and *DominantDimValence* × *Niche*. In Model 3, we added *DominantDimVar* and *DominantDimVar* × *Niche*. Model 3 is our main model, and we used it to report the estimation results and to test our hypotheses. We specified the regression equation of Model 3 as follows:

$$\begin{aligned} LogSales_{i,t} = \ & \beta_1\, InterVar_{i,t-1} \\ & + \beta_2\, DominantDimValence_{i,t-1} \\ & + \beta_3\, DominantDimVar_{i,t-1} \\ & + \theta_1\, InterVar_{i,t-1} \times Niche_i \\ & + \theta_2\, DominantDimValence_{i,t-1} \times Niche_i \\ & + \theta_3\, DominantDimVar_{i,t-1} \times Niche_i \\ & + \beta_4\, LogVolume_{i,t-1} + \beta_5\, LogPrice_{i,t} \\ & + \beta_6\, Valence_{i,t-1} + \alpha_i + f_t + \varepsilon_{i,t}, \quad (1) \end{aligned}$$

where $i = 1, \ldots, I$ denotes product and $t = 1, \ldots, T$ denotes the time period. We controlled for the product fixed effects α_i as well as the time fixed effects f_t. We allowed review variables to be in one period lag as we believe it is the information that the consumer collects in the past that affects their current product choice.[4] In the analysis, we focused on the coefficient of $InterVar_{i,t-1} \times Niche_i$ (i.e., θ_1) when we tested H1. To test H2, we performed a statistical analysis on θ_2, the coefficient term $DominantDimValence_{i,t-1} \times Niche_i$. We examined the coefficient of the interaction term $DominantDimVar_{i,t-1} \times Niche_i$ (i.e., θ_3) to test H3.

Estimation Results

We report our regression results in Columns 1 to 3 in Table 2. All three models produce largely consistent estimation results. In all three models, *LogVolume* (β_4 = 0.461, p < 0.01) is positively associated with log monthly sales, and an increase in the *LogPrice* is associated with a decrease in product sales (β_5 = -.216, p < 0.05). The significantly negative coefficient on *InterVar* (β_1 = -8.153, p < 0.01) and the significantly positive coefficient on *InterVar* × *Niche* (θ_1 = 7.673, p < 0.01) indicate that the effect of *InterVar* on log sale volume is moderated by product type. The impact of *InterVar* on product sales is more negative for mainstream products than for niche ones, supporting H1. We find that the coefficient on *DominantDimValence* is insignificant (β_2 = -.596, *n.s.*), and the interaction effect between *DominantDimValence* and *Niche* (θ_2 = 1.444, p < 0.05) is positive and significant. This result suggests that the rating valence on the dominant dimension positively affects product sales for niche products but not for mainstream products, lending support for H2. The interaction effect between *DominantDimVar* and *Niche* (θ_3 = -1.122, p < 0.1) is negative, consistent with our prediction for H3.

[4] We included the current price instead of the lagged price in the regression analysis. We conducted a robustness check by including the lagged price instead of the current price as a control variable. Estimation results remained consistent in terms of signs and significance levels.

Table 2. Regression Results with Log Sales Volume

	Dependent variable: LogSales		
	(1)	(2)	(3)
InterVar	-7.400*** (-9.463, -5.338)	-9.007*** (-11.290, -6.723)	-8.153*** (-10.738, -5.567)
InterVar × Niche	7.000*** (4.796, 9.203)	8.709*** (6.255, 11.164)	7.673*** (4.942, 10.404)
DominantDimValence		-.932** (-1.796, -.068)	-.596 (-1.573, .380)
DominantDimValence × Niche		2.002*** (.943, 3.060)	1.444** (.208, 2.680)
DominantDimVar			.809 (-.368, 1.987)
DominantDimVar × Niche			-1.122* (-2.398, .155)
Valence	.085 (-.514, .685)	.376 (-.347, 1.100)	.278 (-.495, 1.052)
LogVolume	.454*** (.372, .537)	.454*** (.370, .538)	.461*** (.374, .548)
LogPrice	-.218** (-.434, -.002)	-.212* (-.427, .004)	-.216** (-.432, -.0004)
Product fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R^2	.6885	.6891	.6893
Adjusted R^2	.6712	.6718	.6719
Observations	7,272	7,272	7,272

Note: 95% confidence intervals reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To ensure the robustness of our results, we conducted sensitivity analyses with different criteria applied in terms of the number of products included in the analysis. In robustness checks, we included products with average sales volume greater than 50 and 25 as cutoffs. Our main results remained qualitatively the same and the hypotheses were all supported. We report estimation results from these alternative samples in Table B3 and Table B4 in the Appendix.

Overall, the secondary archival data analysis provides associational evidence that interdimensional rating variance, as well as the intradimensional rating valence and variance for the dominant dimension, matters differently for mainstream vs. niche products. In the next section, we seek to further enhance the causal interpretation of the findings through a series of lab experiments.

Experimental Studies

To enhance the causal interpretation of the results, we conducted three randomized lab experiments. Unlike field studies that have a high external validity, lab experiments provide strong internal validity, which enabled us to control for confounding factors, thereby isolating the effects of the variables of interest. To guide us in selecting the product category, we conducted interviews with three academic experts and eight undergraduate students. Based on the insights gleaned from these interviews, we determined that the laptop category was suitable for our experimental studies, as it is a familiar product category for experimental subjects—i.e., undergraduate students. Familiarity with the evaluation task is important because it allows us to better capture how judgments are formed in a real purchase environment (West & Broniarczyk, 1998). Further, laptops are important yet essential purchases, thereby making the scenarios more realistic.

A panel consisting of senior marketing managers from a well-known computer equipment company and 18 undergraduate students contributed to the development of the experimental scenarios, manipulations, and measures. After an in-depth discussion, for the three lab experiments, we designed scenarios asking participants to imagine a specific purchase need—i.e., in the niche product condition, we asked subjects to imagine that they needed to buy a laptop for big data processing (Experiment 1) / graphic design (Experiment 2) / playing games (Experiment 3); in the mainstream product condition, we asked subjects to imagine that they needed to buy a laptop for daily work and life.

The panel selected four important laptop dimensions as the stimuli for the experiments: appearance, speed, screen, and battery life. They selected speed as the dominant dimension for gaming and big data processing laptops and the screen as the dominant dimension for graphic design laptops. Based on the panel discussion, we manipulated the dominant dimension and the product type (mainstream vs. niche) using several features (hard drive and memory capacity of a big data processing laptop; color gamut and screen resolution of a graphic design laptop; processor and graphics card of a gaming laptop) relevant for determining speed and the screen (details of the experiments are reported in Appendices C-E).

In all three experiments, we presented participants with multidimensional reviews in which we included the overall rating, review volume, and ratings across four dimensions. As overall product ratings are generally positive for most products (Chevalier & Mayzlin, 2006; Li & Hitt, 2008) and consumers tend to avoid low-rated options for durable products, the average rating in the experiments was set to be consistent with the median of most laptops on review platforms, i.e., 8.1 out of 10. Twenty-one undergraduate students from a large public university in China completed a pretest to evaluate the clarity and appropriateness of the experimental scenario and the wording used in the following experiments.

Experiment 1 (Testing H1)

Purpose, design, participants, and procedure: To test H1, we designed and implemented Experiment 1 to examine the effects of interdimensional rating variance and product type on purchase intention. The study employed a between-subjects design in which we adopted two factors, each having two conditions: interdimensional rating variance (low vs. high) and product type (mainstream vs. niche). Two hundred and forty undergraduate students from a large public university in China were recruited to participate in the experiment on purchasing a laptop for daily usage or for big data processing. Each participant received monetary compensation and was assigned to one of the four conditions, with 60 participants in each condition. Fourteen participants who responded incorrectly to the instructional manipulation check (Oppenheimer et al., 2009) were excluded from the analyses, leaving 226 participants for the data analyses (96 men, Mean [*M*] age = 20.98, Standard Deviation [*SD*] age = 0.83). Details of the experimental procedure are reported in Appendix C.

Measures and manipulation checks: Purchase intention was measured using a three-item, 7-point, Likert-type scale drawn from prior research (Wu & Lee, 2016) and included items such as, "Given the information shown, how likely would you be to purchase this laptop?" "How inclined are you to purchase this laptop?" "How willing are you to purchase this laptop?" (1 = *not at all*, 7 = *very much*). We measured the importance of the selected four dimensions, respectively, by asking participants the importance of the dimension in their actual purchase decisions using 7-point scales (1 = *not at all important*, 7 = *very important*) drawn from Sujan and Bettman (1989). As a manipulation check, participants were asked to indicate their perceptions of the interdimensional rating variance, using a scale from 1 (*very low*) to 7 (*very high*).

Participants answered three sets of questions to verify the success of our experimental manipulations on product type. First, participants indicated the extent to which they agreed with the statements: "Laptop A is designed to cater to a specialized segment of the laptop market," and "Laptop A is designed to cater to the needs of consumers of mainstream products (reverse coding)." Responses to the two items were averaged ($r = 0.80$). Second, we asked participants: "Upon seeing the above product introduction, which of the following four dimensions (appearance, speed, screen, and battery life) is the dominant dimension of Laptop A?" Third, participants indicated how similar or different they perceived Laptop A to be from the laptop category in speed (level of discrepancy of the dominant dimension). They responded on two scales (completely identical/completely different; completely similar/not at all similar, reverse coding) drawn from prior research (Sujan & Bettman, 1989), and responses were averaged for analysis ($r = 0.78$).

Results: The manipulation check shows the participants' perceived interdimensional rating variance was higher in the high-variance condition than in the low-variance condition ($M_{\text{high-variance}} = 5.42$, $SD_{\text{high-variance}} = 1.07$ vs. $M_{\text{low-variance}} = 3.47$, $SD_{\text{low-variance}} = 1.92$; $F(1, 224) = 89.29$, $p < 0.001$). Product type was also successfully manipulated as follows. First, participants' agreement on the product designed to cater to a specialized segment of the market was higher in the niche product condition than in the mainstream product condition ($M_{\text{niche}} = 5.64$, $SD_{\text{niche}} = 0.99$ vs. $M_{\text{mainstream}} = 4.71$, $SD_{\text{mainstream}} = 1.19$; $F(1, 224) = 41.35$, $p < 0.001$). Second, all participants identified the dominant dimension of Laptop A in the scenario as speed. Third, participants perceived the level of discrepancy of the dominant dimension (speed) from the laptop category to be stronger in the niche condition than in the mainstream condition ($M_{\text{niche}} = 5.48$, $SD_{\text{niche}} = 0.76$ vs. $M_{\text{mainstream}} = 4.76$, $SD_{\text{mainstream}} = 1.32$; $F(1, 224) = 25.58$, $p < 0.001$).

We conducted a 2 (interdimensional rating variance: high vs. low) × 2 (product type: mainstream vs. niche) ANCOVA on the average of the three-item purchase intention measure (Cronbach's $\alpha = 0.96$), and the importance of the four dimensions (appearance, speed, screen, and battery life) was entered as covariates. The two-way ANCOVA revealed a main effect of product type (F (1, 218) = 7.29, $p < 0.01$) and a main effect of interdimensional rating variance (F (1, 218) = 4.46, $p < 0.05$).

Notably, consistent with predictions, we found a significant interaction effect between interdimensional rating variance and product type (F (1, 218) = 13.80, $p < 0.001$). Planned follow-up contrasts revealed that in the mainstream product condition, purchase intention was lower when interdimensional rating variance was high rather than low ($M_{\text{high-variance}}$ = 4.10, $SD_{\text{high-variance}}$ = 0.60 vs. $M_{\text{low-variance}}$ = 4.86, $SD_{\text{low-variance}}$= 1.39; F (1, 218) = 13.23, $p < 0.001$). In the niche product condition: however, no significant difference in purchase intention was found between high and low interdimensional rating variances ($M_{\text{high-variance}}$ = 5.02, $SD_{\text{high-variance}}$ = 1.12 vs. $M_{\text{low-variance}}$ = 4.72, $SD_{\text{low-variance}}$= 1.19; F (1, 218) = 2.09, *n.s.*). The pattern of means for purchase intention is depicted in Figure 1. These results support H1.

Experiment 2 (Testing H2)

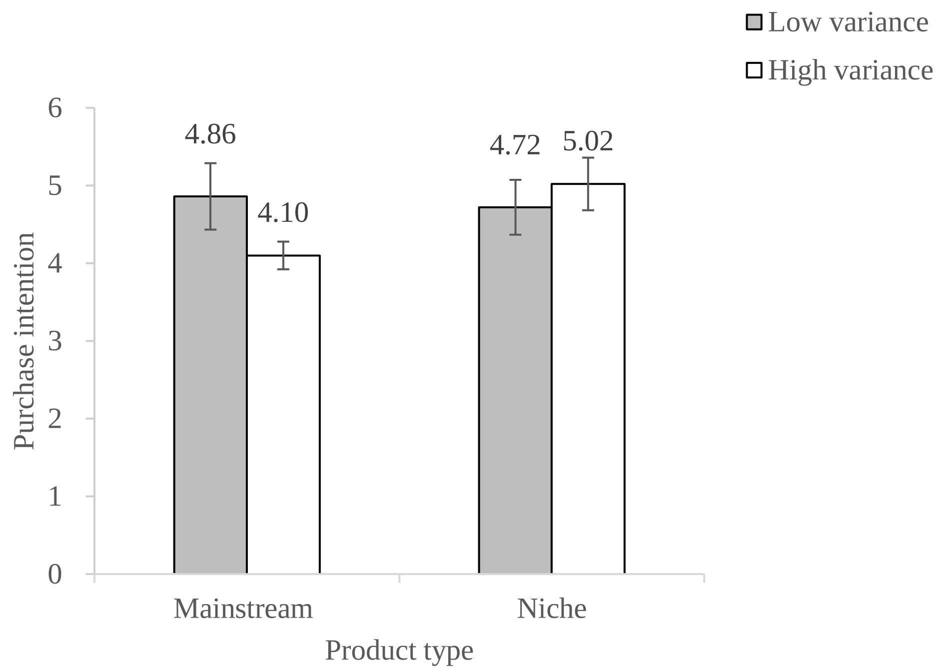
Purpose, design, participants, and procedure: To effectively test H2, Experiment 2 examined the combined effects of intradimensional rating valence on the dominant dimension and product type on purchase intention. In Experiment 2, we varied the dominant dimension to be screen instead of speed. The study again incorporated a between-subjects design in which we adopted two factors, each with two conditions: intradimensional rating valence on the dominant dimension (low vs. high) and product type (mainstream vs. niche). Again, 240 undergraduate students from a large public university in China were recruited to participate in the experiment on purchasing a laptop for daily usage or for graphic design. Each participant received monetary compensation and was randomly assigned to one of the four conditions, with 60 participants in each condition. Twenty-two participants who responded incorrectly to the instructional manipulation check (Oppenheimer et al. 2009) were excluded from the analyses, leaving 218 participants for the data analyses (111 men, M age = 20.70, SD age = 1.39). The details of the experimental procedure are provided in Appendix D.

Measures and manipulation checks: The measures of purchase intention and the importance the four selected dimensions were assessed using the same items as in Experiment 1. As a manipulation check, participants were asked to indicate their perceptions of the intradimensional rating valence on the dominant dimension of the product, using a scale from 1 (*very low*) to 7 (*very high*). Participants answered three sets of questions to verify the success of our experimental manipulations on product type—identical to those used in Experiment 1—except that the participants had to indicate how similar or different they perceived Laptop A to be from the laptop category in terms of the screen instead of speed (level of discrepancy of the dominant dimension) in the third set of questions.

Results. The manipulation check of the intradimensional rating valence on the dominant dimension of the product shows that participants perceived the rating to be higher in the high-rating condition than in the low-rating condition ($M_{\text{high-rating}}$ = 5.28, $SD_{\text{high-rating}}$ = 1.27 vs. $M_{\text{low-rating}}$ = 3.98, $SD_{\text{low-rating}}$ = 1.57; F(1, 216) = 44.97, $p < 0.001$). Product type was also successfully manipulated as follows. First, participants' agreement on the product designed to cater to a specialized segment of the market was higher in the niche product condition than in the mainstream product condition (M_{niche} = 5.61, SD_{niche} = 1.05 vs. $M_{\text{mainstream}}$ = 4.54, $SD_{\text{mainstream}}$ = 1.36; F(1, 216) = 43.07, $p < 0.001$). Second, all participants identified the dominant dimension of Laptop A in the scenario as the screen. Third, participants perceived the level of discrepancy of the dominant dimension (screen) from the laptop category to be stronger in the niche condition than in the mainstream condition (M_{niche} = 5.56, SD_{niche} = 0.67 vs. $M_{\text{mainstream}}$ = 4.37, $SD_{\text{mainstream}}$ = 1.39; F(1, 216) = 67.67, $p < 0.001$).

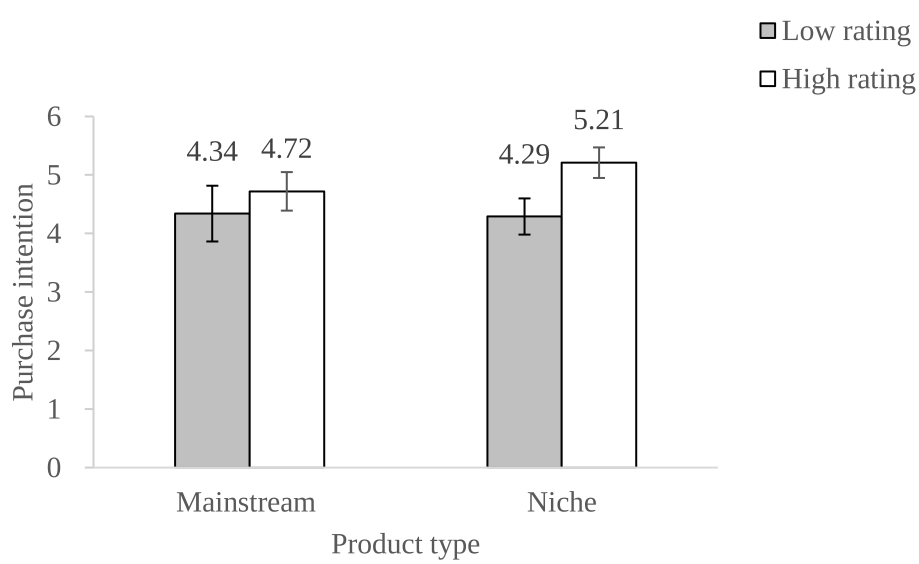
We conducted a 2 (intradimensional rating valence on the dominant dimension: low vs. high) × 2 (product type: mainstream vs. niche) ANCOVA on the average of the three-item purchase intention measure (Cronbach's $\alpha = 0.92$), and again controlled for the importance the four dimensions (appearance, speed, screen, and battery life) as covariates. The two-way ANCOVA revealed a significant main effect of intradimensional rating valence on the dominant dimension (F (1, 210) = 18.66, $p < 0.001$).

Consistent with our predictions, the ANCOVA showed that the interaction effect between the dominant dimension rating and product type was significant (F (1, 210) = 5.19, $p < 0.05$). Planned contrast analysis revealed that for the niche product condition, participants assigned a higher purchase intention for products with a high intradimensional rating valence on the dominant dimension than for products with a low intradimensional rating valence on the dominant dimension ($M_{\text{high-rating}}$ = 5.21, $SD_{\text{high-rating}}$ = 0.88 vs. $M_{\text{low-rating}}$ = 4.29, $SD_{\text{low-rating}}$ = 1.06; F(1, 210) = 19.62, $p < 0.001$). However, in the mainstream product condition, the intradimensional rating valence on the dominant dimension had a positive yet insignificant effect on purchase intention ($M_{\text{high-rating}}$ = 4.72, $SD_{\text{high-rating}}$ = 1.03 vs. $M_{\text{low-rating}}$ = 4.34, $SD_{\text{low-rating}}$ = 1.49; F(1, 210) = 2.85, *n.s.*). The pattern of means for purchase intention is depicted in Figure 2. These results support H2.



Note: Error bars reflect 95% confidence intervals.

Figure 1. Purchase Intention as a Function of Interdimensional Rating Variance and Product Type



Note: Error bars indicate 95% confidence intervals.

Figure 2. Purchase Intention as a Function of Intradimensional Rating Valence on the Dominant Dimension and Product Type

Experiment 3 (Testing H3)

Purpose, design, participants, and procedure: To test H3, we designed Experiment 3 to examine the combined effects of the intradimensional rating variance on the dominant dimension and product type on purchase intention. This experiment again incorporated a between-subjects design in which we adopted two factors, each of which had two conditions: the intradimensional rating variance on the dominant dimension (low vs. high) and product type (mainstream vs. niche). Again, 240 undergraduate students from a large public university in China were recruited to participate in the experiment regarding purchasing a laptop for daily usage or for gaming. Each participant received monetary compensation and was assigned to one of the four conditions, with 60 participants in each condition. Six participants who responded incorrectly to the instructional manipulation check (Oppenheimer et al., 2009) were excluded from the analyses, leaving 234 participants for the data analyses (100 men, M age =21.46, SD age = 0.93). The details of the experimental procedure are provided in Appendix E.

Measures and manipulation checks: The measures of purchase intention and importance the selected four dimensions were assessed using the same measurement items as in Experiment 1. As a manipulation check, participants were asked to indicate their perceptions of the intradimensional rating variance on the dominant dimension, using a scale from 1(*very low*) to 7 (*very high*). Participants also answered three sets of questions to verify the success of our experimental manipulations on product type, identical to the procedure implemented in Experiment 1.

Results: The manipulation check shows that participants' perceived intradimensional rating variance was higher in the high-variance condition than in the low-variance condition ($M_{\text{high-variance}} = 5.03$, $SD_{\text{high-variance}} = 1.22$ vs. $M_{\text{low-variance}} = 3.88$, $SD_{\text{low-variance}} = 1.30$; $F(1, 232) = 48.21$, $p < 0.001$). Product type was also successfully manipulated as follows: First, participants' agreement on the product designed to cater to a specialized segment of the market was higher in the niche product condition than in the mainstream product condition ($M_{\text{niche}} = 5.68$, $SD_{\text{niche}} = 0.85$ vs. $M_{\text{mainstream}} = 3.66$, $SD_{\text{mainstream}} = 1.49$; $F(1, 232) = 163.33$, $p < 0.001$). Second, all participants identified the dominant dimension of Laptop A in the scenario as speed. Third, participants perceived the level of discrepancy of the dominant dimension (speed) from the laptop category as stronger in the niche condition than in the mainstream condition ($M_{\text{niche}} = 5.40$, $SD_{\text{niche}} = 0.56$ vs. $M_{\text{mainstream}} = 4.14$, $SD_{\text{mainstream}} = 1.23$; $F(1, 232) = 102.62$, $p < 0.001$).

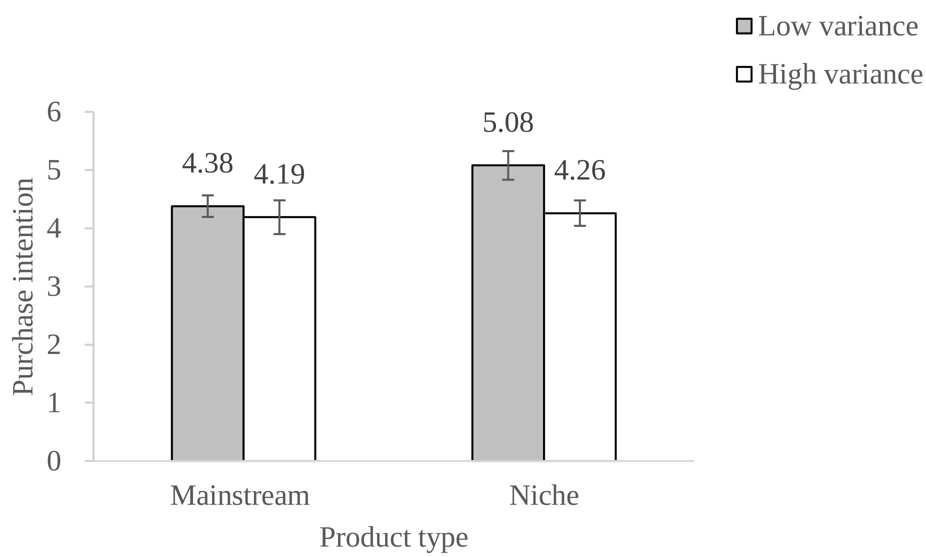
We conducted a 2 (intradimensional rating variance on the dominant dimension: low vs. high) × 2 (product type: mainstream vs. niche) ANCOVA on the average of the three-item purchase intention measure (Cronbach's $\alpha = 0.93$), and controlled for the importance the four dimensions (appearance, speed, screen, and battery life) as covariates. The two-way ANCOVA revealed a significant main effect of intradimensional rating variance on the dominant dimension ($F(1, 226) = 22.15$, $p < 0.001$) and a significant main effect of product type ($F(1, 226) = 13.18$, $p < 0.001$).

Consistent with our predictions, we found a significant interaction effect between the intradimensional rating variance on the dominant dimension and product type ($F(1, 226) = 8.00$, $p < 0.01$). Planned follow-up contrasts revealed that for the niche product condition, participants reported a higher purchase intention for products with low intradimensional variance than for products with high-dimensional variance ($M_{\text{low-variance}} = 5.08$, $SD_{\text{low-variance}} = 0.83$ vs. $M_{\text{high-variance}} = 4.26$, $SD_{\text{high-variance}} = 0.75$; $F(1, 226) = 30.67$, $p < 0.001$). However, in the mainstream product condition, intradimensional variance had no significant effect on purchase intention ($M_{\text{low-variance}} = 4.38$, $SD_{\text{low-variance}} = 0.63$ vs. $M_{\text{high-variance}} = 4.19$, $SD_{\text{high-variance}} = 0.97$; $F(1, 226) = 1.64$, *n.s.*). The pattern of the means of purchase intention is depicted in Figure 3. These results support H3.

Discussion

Contributions to the Literature

Our findings offer several important contributions to the extant literature on online reviews. First, to the best of our knowledge, the current work is the first to distinguish the two types of distinct variances (i.e., interdimensional rating variance and intradimensional rating variance on the dominant dimension) and examine how they affect product sales differently for mainstream vs. niche products. The interdimensional rating variance indicates cross-dimension evaluation inconsistency and shows the dispersion of dimension values within each product, whereas the intradimensional rating variance on the dominant dimension of a product indicates inconsistent evaluations among reviewers on the dominant dimension. Previous research has only examined the variance in the overall product rating across reviewers. For example, He and Bond (2015) focused on cross-reviewer variance in the overall product rating and found that consumer interpretation of review variance depends on the extent to which tastes in a product domain are perceived as dissimilar. The decomposition of the variances that naturally arise in the multidimensional choice expands our understanding of the mixed findings regarding the effect of rating variances on sales (e.g., Clemons et al., 2006; Moe & Trusov, 2011; Sun, 2012; Wang et al., 2015; Zhu & Zhang, 2010).



Note: Error bars reflect 95% confidence intervals.

Figure 3. Purchase Intention as a Function of Intradimensional Rating Variance on the Dominant Dimension and Product Type

Second, this study emphasizes the product type—more specifically, mainstream vs. niche products—as an important contextual variable to examine the contingent effect of multidimensional review evaluations on product sales. While previous studies on online reviews have mentioned different product categories (Sun, 2012; Wang et al., 2015; Zhu & Zhang, 2010), they have limited their focus to an overall-rating-based analysis. Overall product rating indicates how much previous buyers like the focal product in general but does not convey the review information on different product dimensions. Specifically, we found that in the multidimensional review context, consumers of niche products are more likely to focus on the performance information (intradimensional rating valence and variance) of the dominant dimension, as both a higher rating valence and a lower rating variance on the dominant dimension generate higher sales for niche products. In contrast, consumers of mainstream products are more sensitive to the interdimensional variance for each product; high interdimensional rating variance is more detrimental to product sales for the mainstream market than for the niche market. Building on the emerging work on multidimensional rating systems (Chen et al., 2018; Liu & Karahanna, 2017; Schneider et al., 2021), this study advances our understanding of the nuanced effects of multidimensional online reviews on product sales by revealing how the features (valence and variance) of multidimensional reviews impact product sales differently for mainstream versus niche products.

Third, we report a first study on the impact of the dominant dimension on product sales in the context of multidimensional rating systems. We differentiate the product rating on its dominant dimension from the overall product review metrics such as overall product rating valence and variance (e.g., Chevalier & Mayzlin, 2006; Sun, 2012) and show the explanatory power of the dominant dimension rating valence and variance in predicting product sales. As previous studies have shown that multidimensional rating systems are superior to single-dimensional rating systems in that they generate higher satisfaction (Chen et al., 2018), this study provides a basis for future studies on the impact of dimension-level review characteristics.

Contributions to the Practice

Our research provides actionable managerial insights for both product providers (firms) and their review platforms. First, from the firm perspective, firms should proactively monitor how their products are evaluated under multidimensional rating systems to gain insights into their consumers as well as their competitors. Tracking the dimension-level ratings of their products and their competitors' products can help them to develop appropriate strategies for product positioning, quality improvement, and marketing communication in order to improve sales.

Second, the demonstrated effects of dimension-specific online reviews on product sales provide firms with critical information that can help set priorities in allocating resources to improve product quality and consumer satisfaction. Based on dimension-level rating performance in the overall product category, firms can design more effective competitive strategies. Specifically, firms of niche product offerings should prioritize resources to improve product performance (i.e., higher rating and lower variance) on the dominant dimension in order to outperform their competitors. However, for mainstream products, firms should prioritize resources to improve the performance of the lowest-rated dimension so that they can reduce the interdimensional variance.

Third, although firms might not be able to manipulate online reviews, they can decide which information to focus on in their communications (Wang et al., 2015). Specifically, if the interdimensional variance is low, firms targeting a mainstream market should highlight this information to potential buyers by promoting the product as a winner with more balanced, all-dimension performance. Firms targeting a niche market, on the other hand, should emphasize the superiority of the product (high rating and low rating variance) on its dominant dimension to generate higher consumer interest and preference.

For review platforms, first, we provide insights into the effective design of multidimensional rating systems to facilitate the generation and exchange of product information on dimension-level performance. Given that multidimensional ratings provide important information to consumers, platforms should conduct large-scale testing to configure the optimal mix of dimensions for representing a product category and incentivize users to submit their ratings on individual product dimensions.

Second, our results suggest that online review platforms should saliently distinguish niche products from mainstream products when presenting rating information to users. Such distinctions may help potential buyers identify whether a specific product is for a mainstream market or for a niche market, reducing decision costs generated by information overload and helping consumers more efficiently construct a consideration set (Levy et al., 2013).

Third, our findings suggest when online review platforms calculate overall ratings, the rating valence and variance on the dominant dimension should carry more weight for niche products, while the cross-dimension variance should carry more weight for mainstream products.

Limitations and Future Research

We acknowledge several limitations of this research, which opens avenues for future research. First, although the results from our paper may apply to a wider set of products, we solely focused on two durable product categories: automobiles and laptops. The applying context of this study should be markets that have highly differentiated products. In such markets, consumers face trade-offs in dimension performance in their purchase decisions. They are likely to adopt different evaluation strategies based on the product type and the dimension type. Additional empirical evidence from other categories of products or services would be useful in helping establish the generalizability of our findings. Second, future research could devise research designs to explicitly test the underlying mediating mechanisms—for example, using eye-tracking techniques to capture different product evaluation strategies. Lastly, it would be interesting to take a dynamic perspective to examine the impact of multidimensional rating features on product sales over time.

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Appendix A

Qualitative Interviews for the Field Study

To guide our conceptual framework and variable operationalization for the field study, we conducted 15 in-depth interviews with practitioners of the automobile industry: 3 marketing managers of different manufacturers, 6 sales managers of different dealerships, 2 platform managers in charge of the marketing cooperation with manufacturers and dealers, and 4 senior consultants in the automotive marketing field. The interviews lasted between 30 minutes and about 2 hours, and we were permitted to audio-record and transcribe verbatim all the interviews. Following the interview guide approach (Patton, 1990), we structured the interviews around the following four questions: (1) How widely is the online review platform under study used by consumers before purchase? (2) How do you define a mainstream product vs. a niche product? (3) How do you define a dominant dimension? (4) How do consumers evaluate a mainstream product vs. a niche product? Table A1 summarizes the key quotes from our interviewees and the points that are related to our research, which were translated into English by a bilingual person and verified by another bilingual person.

Table A1. Summary of Interview Quotes

Quote #	Interviewee # and description	Quotes	Points related to the current study
1	#3, manufacturer manager	"Platform A is the vertical media that we cooperate with the most, and we invest tens or hundreds of million Chinese yuan each year. We do this because: 1) 30%-40% of our sales leads are from Platform A. 2) Most of our consumers search relevant information (e.g., online reviews) on Platform A before buying a car from us."	Before purchase, consumers widely use the online review system where we obtained the review data.
2	#2, dealer manager	"We've been cooperating with Platform A for a long time. We pay almost 200,000 Chinese *yuan* for the membership and get about 7,500 sales leads each year. Our consumers always search information on Platform A before visiting our store."	Platform A generates many sales leads for dealers, and consumers always check information and compare different vehicle models on Platform A before they visit a dealership.
3	#1, platform manager	"Platform A is the biggest automotive consumption and service platform in China, with partners of over 200 automotive brands and 24,000 dealers. It has 430 million users and generates about 110 million sales leads each year."	The platform ranks first among China's automotive websites and automotive channels of internet portals in terms of average daily unique visitors, average daily time spent per user, and average daily page views.
4	#3, senior consultant	"At present, Platform A is the No. 1 automotive consumption and information service platform in China with a monthly page view of over 40 million hours, greatly surpassing its competitors, and exerts profound influence on consumers."	More consumers are attracted to the platform because it offers more information than its competitors.
5	#1, manufacturer manager	"When we develop and design our products, we tend to highlight the important attribute or feature that represents our brand identity or unique selling point. For a mainstream model, all attributes are relatively balanced, and it also maintains the differentiating feature of our brand. For luxury or niche models, we put more emphasis on special attributes, such as the roomy space of high-end minivans for the business purpose."	The dominant dimension is often used to create a perception of the differences among products in the product category.
6	#4, dealer manager	"When we introduce GL8 to consumers, we emphasize its business purpose and the distinguishing advantages on the space and comfort."	Strong discrepancy of the dominant dimension from the general product category schema leads to a niche product position.
7	#2, senior consultant	"Automobile sellers tend to emphasize a unique selling point that every brand or model hopes to convey to users. BMW is known for the pleasure of driving, while Mercedes is known for the comfort of riding."	Consumers remember products' dominant dimensions better than other dimensions.

8	#2, platform manager	"From the perspective of our platform, we find that the dominant attribute of an automobile is the product attribute that users are most willing to make comments on our platform. For example, most Volkswagen Beetle owners express their satisfaction with the exterior styling of their cars when writing reviews."	Consumers remember products' dominant dimensions better than other dimensions and therefore often comment on them in their reviews.
9	#2, manufacturer manager	"Most of our cars are mainstream product. For instance, Lavida has moderate performance in all aspects and owns Volkswagen's brand features. In addition, we also have niche models like the Beetle. It has unique exterior styling favored by a specific group, so we need to target such consumers."	Mainstream products are targeted to a broad segment in a product category by using the dominant dimension, which is perceived not to be strongly discrepant from the general product category schema from the firm's perspective. Strong discrepancy of the dominant dimension from the general product category schema leads to a niche product position.
10	#1, dealer manager	"As a luxury-brand 4S store, our products are mostly niche models. For example, our Mini-Cooper has unique exterior styling, and some female consumers are enthusiastic about our products. Therefore, we highlight the unique product feature that matches these prospects during product recommendation."	Niche products may afford a better defense of the product's competitive position, as the product is seen as isolated from the rest of the market and less likely to be substituted.
11	#5, dealer manager	"Most models of our brand are mainstream products. Products such as Excelle GT, Regal and LaCrosse, have a monthly sales volume of nearly 20,000 and are clearly designed for the mass market, but our GL8 is a niche model. This product is targeted to business people. They want a big space and care less about other attributes such as fuel consumption."	Niche products are targeted to a specific group. Consumers of niche products with particular needs and preferences value the advantages of the dominant dimension but are not very sensitive to its disadvantages.
12	#2, senior consultant	"When we study the automobile products, we found that mainstream products tend to be relatively balanced in all aspects, although they have exclusive characteristics of the brand. Niche products usually have a distinguishing performance in a specific attribute, and many consumers buy them because of their preference for the special attribute. The Buick GL8, for example, is spacious and suits business people. Consumers are willing to buy it despite its high fuel consumption."	A strong discrepancy of the dominant dimension from the general product category schema leads to a niche product position. The mainstream product is targeted to a broad segment in a product category by using the dominant dimension that is perceived not to be strongly discrepant from the general product category schema.
13	#3, dealer manager	"We meet many consumers every day, and we feel that when they buy our cars (a mainstream brand), they prefer our comprehensive good performance in all aspects almost without obvious weakness, and the differentiated features of our brand."	A more balanced, all-dimension evaluation criterion has priority for consumers of mainstream products.
14	#1, senior consultant	"When we did a user survey, we found that mainstream models should make users perceive a more balanced, all-dimension performance. However, niche models should highlight the uniqueness of a particular attribute that strongly outperforms the competitors."	A more balanced, all-dimension evaluation criterion has priority for consumers of mainstream products. Consumers of niche products will arrive at a decision largely based on the performance of the dominant dimension and choose an alternative with the outstanding dominant dimension.
15	#2, platform manager	"Regarding user browsing habits of our platform, they read online reviews of different vehicle models before purchasing. When they found the niche models that they want to buy strongly outperform others in the dominant attribute, it greatly increases their intention to leave personal information."	Consumers of niche products are more likely to adopt a dominant dimension-superiority evaluation strategy.

Appendix B

Descriptive Statistics and Robustness Checks for the Field Study

Table B1. Summary Statistics

Statistic	Mean	*SD*	Min	Max
SalesVolume	3,559.845	5,325.765	1.000	51,242
InterVar	.378	.112	0.000	1.676
Niche	.595	.491	0	1
DominantDimValence	4.449	.404	2.000	5.000
DominantDimVar	.614	.194	0.000	1.639
Valence	4.257	.229	3.286	4.938
Volume	1,162.852	1,525.768	1	16,323
Price (in thousand CNY)	226.726	250.780	25	2,230

Table B2. Correlation Matrix

	Sales volume	InterVar	Niche	DominantDim valence	DominantDim varience	Valence	Volume	Price
SalesVolume	1							
InterVar	-.228	1						
Niche	-.360	.126	1					
DominantDimValence	.013	-.133	-.147	1				
DominantDimVar	.028	.048	.121	-.320	1			
Valence	.119	-.502	.142	.452	.421	1		
Volume	.478	-.092	-.344	-.095	-.111	-.068	1	
Price	-.143	-.009	-.073	.245	-.126	.313	-.239	1

Table B3. Regression Results with Log Sales Volume (Products with Sales Volume Exceeding 50)

	Dependent variable: LogSales		
	(1)	(2)	(3)
InterVar	-7.443*** (-9.516, -5.370)	-8.720*** (-11.006, -6.433)	-7.904*** (-10.487, -5.321)
InterVar × Niche	7.086*** (4.904, 9.268)	8.475*** (6.044, 10.906)	7.727*** (5.015, 10.440)
DominantDimValence		-.791* (-1.656, .074)	-.473 (-1.457, .510)
DominantDimValence × Niche		1.513*** (.501, 2.525)	1.133* (-.052, 2.318)
DominantDimVar			.801 (-.380, 1.983)
DominantDimVar × Niche			-.770 (-2.040, .500)
Valence	.110 (-.477, .697)	.286 (-.415, .988)	.138 (-.610, .885)
LogVolume	.489*** (.406, .571)	.488*** (.404, .573)	.484*** (.397, .571)
LogPrice	-.268** (-.482, -.055)	-.263** (-.477, -.050)	-.268** (-.481, -.054)

Product fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R^2	.7165	.7168	.7169
Adjusted R^2	.7008	.7011	.7011
Observations	7,791	7,791	7,791

Note: 95% confidence intervals reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B4. Regression Results with Log Sales Volume (Products with Sales Volume Exceeding 25)

	Dependent variable: LogSales		
	(1)	**(2)**	**(3)**
InterVar	-7.451*** (-9.513, -5.388)	-9.063*** (-11.350, -6.777)	-8.327*** (-10.901, -5.752)
InterVar × Niche	6.673*** (4.527, 8.818)	8.368*** (5.968, 10.767)	7.272*** (4.611, 9.934)
DominantDimValence		-.848* (-1.711, .015)	-.518 (-1.502, .466)
DominantDimValence × Niche		1.898*** (.905, 2.891)	1.232** (.057, 2.407)
DominantDimVar			.698 (-.480, 1.876)
DominantDimVar × Niche			-1.309** (-2.557, -.061)
Valence	.034 (-.518, .587)	.427 (-.254, 1.107)	.441 (-.281, 1.164)
LogVolume	.514*** (.432, .596)	.507*** (.423, .590)	.525*** (.439, .611)
LogPrice	-.266** (-.477, -.055)	-.259** (-.469, -.048)	-.261** (-.472, -.051)
Product fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
R^2	.7472	.7477	.7479
Adjusted R^2	.7333	.7337	.7339
Observations	8,232	8,232	8,232

Note: 95% confidence intervals reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix C

Experimental Procedure and Stimuli of Experiment 1

Participants in the mainstream product condition and in the niche product condition read the following descriptions, respectively.

Mainstream product condition:

Imagine that you need to buy a laptop for daily work and life, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

It is enough to meet various needs on daily use.

It has a hard drive with good stability and a fast reading/writing speed, large memory capacity, balanced configurations, and superior performance in all product attributes. It will be a tremendous help for your work and life.

Niche product condition:

Imagine you need to buy a laptop for big data processing, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

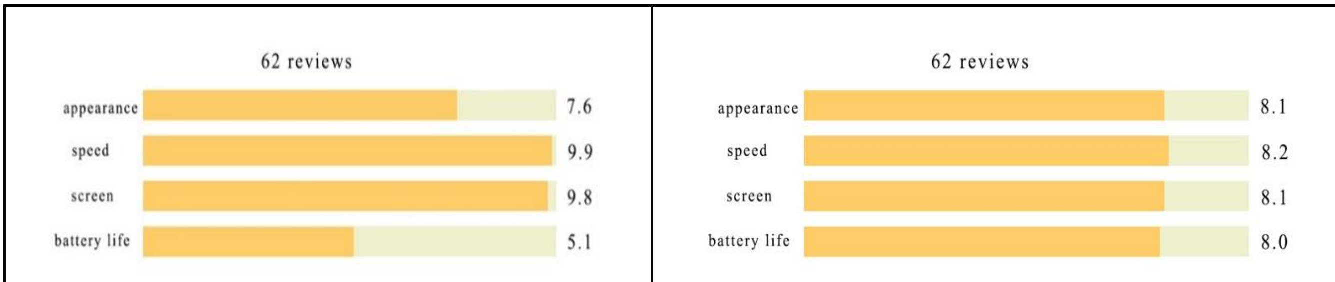
It will be a tremendous help for big data processing and analysis and enough to meet various needs for big data processing.

It has a large-capacity, solid-state hard drive with strong stability, a first-class reading/writing speed, and an ultra-high memory capacity. It can help you process large data sets and conduct intensive big data analyses.

We then presented the following information to all participants:

Laptop A was evaluated by 62 consumers on this popular computer review platform, with an average overall score of 8.1. The following chart shows the average score for the different dimensions (each consumer has an opportunity to evaluate each dimension on a scale of 1-10).

Participants were then presented with a bar chart depicting the dimension-level average rating of each dimension (see Figure C1). Interdimensional rating variance manipulation was constructed with average ratings on four selected dimensions in the order of appearance, speed (the dominant dimension), screen, and battery life. In the high interdimensional rating variance condition, variances were constructed with the following average ratings: 7.6, 9.9, 9.8, and 5.1, whereas in the low interdimensional rating variance condition, variances were constructed with the following ratings: 8.1, 8.2, 8.1, and 8.0, respectively.



High interdimensional rating variance | Low interdimensional rating variance

Figure C1. Stimulus Used in Experiment 1

After viewing the interdimensional rating variance for the laptop, participants responded to purchase intention, manipulation checks, and a set of questions regarding the covariates (i.e., importance of the selected four dimensions). Participants also indicated their gender and age.

Appendix D

Experimental Procedure and Stimuli of Experiment 2

Participants in the mainstream product condition and in the niche product condition read the following descriptions, respectively.

Mainstream product condition:

Imagine that you need to buy a laptop for daily work and life, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

It is enough to meet various needs for daily use.

It has a wide-color gamut display screen, high-definition screen resolution, balanced configurations, and superior performance in all product attributes. It will be a tremendous help for your work and life.

Niche product condition:

Imagine you need to buy a laptop for graphic design, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

It will meet various graphic design needs.

It has an ultra-wide color gamut display screen and a 4K ultra-high-definition screen resolution. It captures image details clearly, presents images with rich and authentic colors, and processes images smoothly.

We then presented the following information to all participants:

Laptop A was evaluated by 62 consumers on this popular computer review platform with an average overall score of 8.1. The following chart shows the average score for its different dimensions (each consumer has an opportunity to evaluate each dimension on a scale of 1-10).

Participants were then shown a bar chart depicting the dimension-level average rating of each dimension (see Figure D1). An intradimensional rating valence on the dominant dimension manipulation was constructed with average ratings on four selected dimensions in the order of appearance, speed, screen (the dominant dimension), and battery life. In the high intradimensional rating valence on the dominant dimension condition, variances were constructed with the following average ratings: 7.6, 9.8, 9.9, and 5.1, whereas in the low intradimensional rating valence on the dominant dimension condition, they were constructed with the following ratings: 7.6, 9.8, 5.1, and 9.9, respectively.

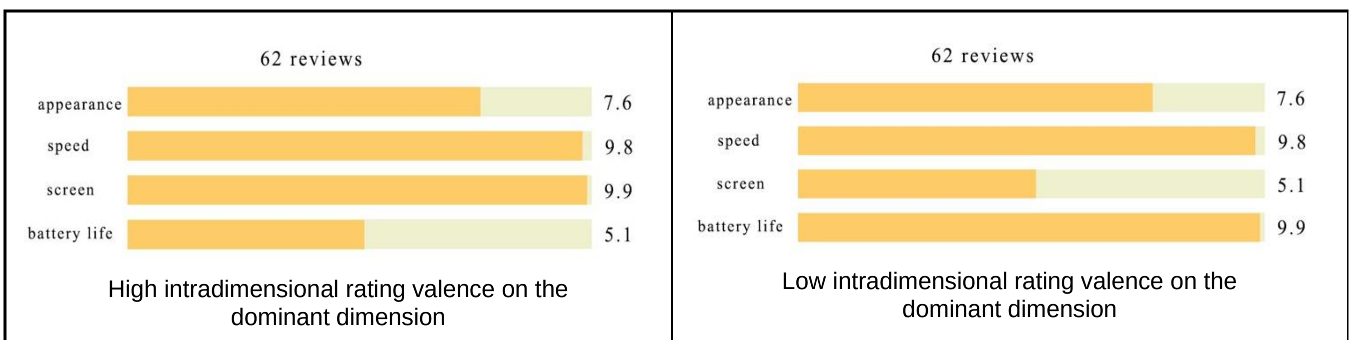


Figure D1. Stimulus Used in Experiment 2

After viewing the interdimensional rating variance for the laptop, participants responded to purchase intention, and a set of questions regarding the covariates (i.e., importance of the selected four dimensions). Participants also indicated their gender and age.

Appendix E

Experimental Procedure and Stimuli of Experiment 3

Participants in the mainstream product condition and the niche product condition read the following description, respectively.

Mainstream product condition:

Imagine you need to buy a laptop for daily work and life, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

It is enough to meet various needs for daily use.

It has the latest processor and a discrete graphics card, balanced configurations, and superior performance in all product attributes. It would be helpful for your work and life.

Niche product condition:

Imagine you need to buy a laptop for playing games, and you see the following product introduction of Laptop A on a well-known computer review platform (price: 5,299 Chinese yuan):

It is enough to meet various needs to freely play games.

It has a high-end processor and a top-level graphics card. The overall game performance has been improved by 70%. Almost all games can be run smoothly, and users will enjoy an excellent gaming experience.

We then presented the following information to all participants:

Laptop A was evaluated by 62 consumers on this popular computer review platform, with an average overall score of 8.1. The following chart shows the average score for its different dimensions (each consumer has an opportunity to evaluate each dimension on a scale of 1-10).

Participants were then presented with a bar chart depicting the dimension-level average ratings on four selected dimensions in the order of appearance (8.7), speed (9.1), screen (9.0), and battery life (5.4) (see Figure E1).

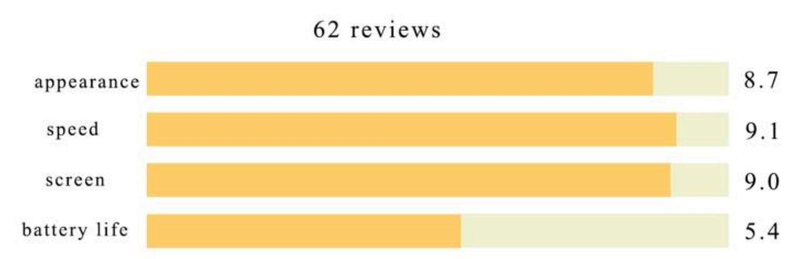
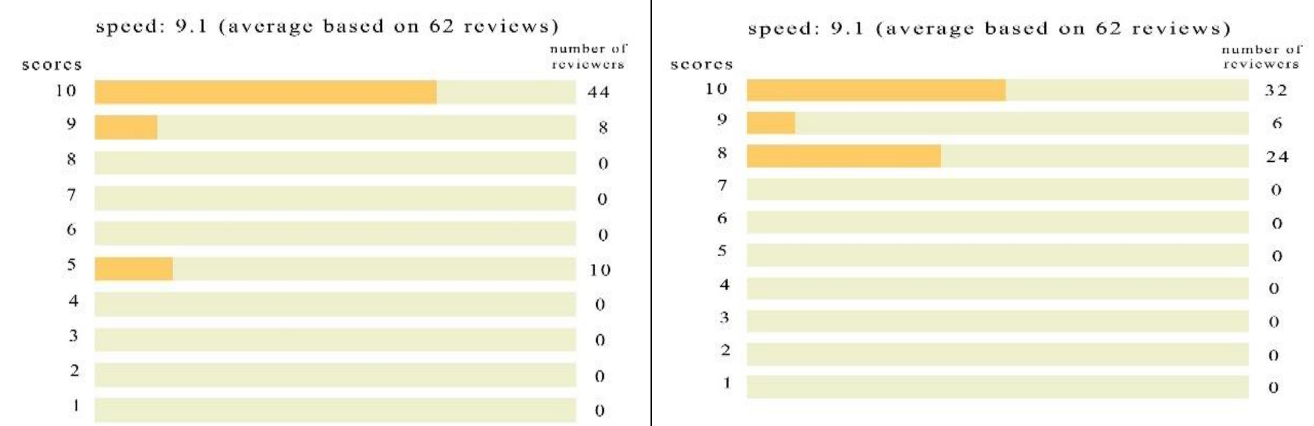


Figure E1. Dimension-Level Average Ratings Used in Experiment 3

Participants were shown a chart depicting intradimensional rating variance on the dominant dimension (speed). In the high intradimensional rating variance condition, variances were constructed with the following ratings: 10, 9, and 5, whereas in the low intradimensional rating variance condition, they were constructed with the following ratings: 10, 9, and 8 (see Figure E2).



High intradimensional rating variance on the dominant dimension

Low intradimensional rating variance on the dominant dimension

Figure E2. Stimulus Used in Experiment 3

After viewing the interdimensional rating variance for the laptop, participants responded to purchase intention, and a set of questions regarding the covariates (i.e., the importance of the selected four dimensions). Participants also indicated their gender and age.