

The Effects of Electronic Word-of-Mouth and Online Observational Learning Information on Customer Decision-Making: Evidence from High- and Low-Premium Smartphones on Taobao

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Keywords: Electronic word-of-mouth; observational learning; online reviews; customer decision-making; brand premium; smartphone; Taobao

Abstract: Online shoppers decide under two kinds of social information: electronic word-of-mouth (eWOM), which conveys other consumers' opinions, and observational learning (OL) information, which conveys their actions, such as sales and review counters. This paper examines how the two relate to customer decision-making and whether their influence depends on brand premium. Using 90 days of daily data (1 January–31 March 2018) on two smartphones sold through the same official flagship store on Taobao—the high-premium Apple iPhone X and the low-premium Huawei Honor V9—we decompose 6,239 screened reviews into seven content dimensions (authenticity, appearance, function and performance, young-user references, older-user references, logistics and customer service) and relate them to sales. Three findings emerge. First, review content differs systematically: iPhone X reviews are dominated by authenticity, performance and young-user references, Honor V9 reviews by older-user references, logistics and service. Second, opinion-based eWOM content is strongly associated with sales for both products, function-and-performance content most of all ($r = 0.935$ and 0.899), whereas the action-based OL cue of review volume tracks sales only loosely. Third, brand premium conditions which dimensions matter: in multivariate models only function and young-user content are positively associated with iPhone X sales, whereas function, logistics and service content are positively associated with Honor V9 sales. Premium-brand customers thus rely on a narrow set of product-centred cues, while for mass-market brands service-related eWOM carries additional decision-relevant information. Implications and limitations are discussed.

1. Introduction

The diffusion of e-commerce has changed not only where consumers buy but how they decide.

Because online shoppers cannot inspect a product physically or consult a salesperson, they rely to an unprecedented degree on information generated by other consumers and displayed on the product page [1,2]. Chinese platforms have amplified this reliance by exposing, alongside written reviews, an array of aggregate indicators—sales counters, cumulative review counts, positive and negative review rates, and keyword-level tag statistics—so that a shopper can see at a glance both what previous buyers said and how many of them there were. Reading these signals before deciding whether to buy has become a routine element of online purchasing, and firms in turn use review platforms to disseminate information, collect feedback, cultivate potential customers and build brands at low cost.

Research on online consumer behaviour has established that the information on a product page is of two kinds, and that they influence decisions through different mechanisms [3]. Electronic word-of-mouth (eWOM) consists of opinions: consumers' written evaluations of the product, the seller and the service, with reasons attached [4,5]. Observational learning (OL) information consists of actions: signals of what other consumers have done, such as how many units have been sold or how many buyers have posted reviews, without any stated reason [6,7]. Opinions are richer but also noisier and less credible, because they are anonymous and may be manipulated; actions are coarser but harder to fake and are commonly read as evidence of quality through social proof. Chen et al. [3] show that the two influence sales differently, and that negative opinions and positive actions have asymmetric effects. Yet most empirical studies of online reviews in China still treat review volume and review valence as the whole of "online word-of-mouth", without separating the opinion content of reviews from the action information that review and sales counters convey, and without asking whether the balance between the two depends on the product.

The present paper addresses these gaps in the context of the smartphone market, the largest single category of consumer electronics sold online in China and one in which products span a wide range of brand premium within a single functional class. We study two smartphones sold through the same official flagship store on Taobao during the first quarter of 2018: the Apple iPhone X, a high-premium product launched two months earlier, and the Huawei Honor V9, a mass-market product with a low brand premium. For each we collect daily sales together with the full set of online reviews, decompose review text into seven content dimensions by keyword frequency, and relate the dimensions and review volume to sales. The design allows us to ask three questions. (1) Do consumers of high- and low-premium products generate and attend to different kinds of eWOM content? (2) Which is more closely associated with purchase decisions—the opinion content of reviews (eWOM) or the action-based cue of how many reviews have been posted (OL information)? (3) Does the brand premium of the product change which content dimensions are decision-relevant?

The paper contributes to the literature in three ways. First, it applies the opinion-versus-action distinction of Chen et al. [3] to a Chinese platform on which action information is unusually salient, using content-decomposed reviews rather than aggregate valence. Second, it introduces brand premium as a moderating condition, showing that the decision-relevant dimensions of eWOM are not fixed but shift from product-centred cues for premium brands to service-centred cues for mass-market brands. Third, by exploiting reviews that reveal the intended user of the purchased phone (references to a girlfriend or wife versus to parents or the elderly), it links the segmentation of buyers to the information they rely on, which is rarely possible with platform data alone.

The remainder of the paper proceeds as follows. Section 2 reviews the theoretical background and develops hypotheses. Section 3 describes the research design, data and variables. Section 4 reports the results. Section 5 discusses the findings, and Section 6 concludes with implications and limitations.

2. Theoretical background and hypotheses

2.1 Electronic word-of-mouth

Word-of-mouth is informal, non-commercial communication between people about products, prices and services [8]. Its online counterpart, eWOM, is defined as any positive or negative statement made by potential, actual or former customers about a product or company that is made available to a multitude of people via the internet [4]. eWOM differs from traditional word-of-mouth in five respects that matter for decision-making: it spreads far beyond the face-to-face dyad and at far greater speed [5]; it is largely anonymous, which frees senders to speak but lowers the credibility of what they say [9]; it is asynchronous, so that sender and receiver need not coincide in time; it is interactive, allowing receivers to solicit opinions rather than merely receive them; and it is persistent and searchable, leaving a record that can be revisited and extended long after the event. Together these features make eWOM cheaper to obtain, wider in reach and more durable than traditional word-of-mouth, but also more open to noise and manipulation.

Two streams of research bear on how eWOM affects purchase decisions. The first, following Hovland's model of persuasion, decomposes eWOM influence into the source, the message, the receiver and the relationship among them: the expertise of the sender and the strength of the tie between sender and receiver, the credibility of the hosting website, and the receiver's trust propensity, expertise and perceived risk [9,10]. Because the tie between anonymous reviewers and readers is weak, online reviews are generally less credible than traditional word-of-mouth [10]; at the same time, information from other consumers is perceived as more neutral and less commercial than information from sellers, and is therefore more readily accepted [10]. The second stream examines valence. Negative eWOM is typically more influential than positive eWOM [8,11], because consumers trust negative information more, seek it out, and find it more diagnostic; the effect is stronger for experience goods than for search goods and is moderated by product involvement [12,13].

2.2 Observational learning information

A second body of theory concerns learning from the actions rather than the opinions of others. Social learning theory holds that individuals acquire behaviour by observing the behaviour of others and its consequences [14]. In economics, models of informational cascades show that when agents observe predecessors' choices but not their private information, it can be rational to follow the crowd and disregard one's own signal, producing herding [6,15]. Field experiments confirm that consumers respond to displayed popularity: Cai et al. [7] find that informing diners which dishes are best-sellers raises demand for those dishes, and Chen et al. [3] show, in a natural experiment on Amazon, that OL information—the observed purchase behaviour of others—affects sales independently of, and differently from, word-of-mouth.

On Chinese e-commerce platforms OL information is exceptionally salient. Every listing displays a sales counter and a cumulative review count, and because reviews can be posted only by buyers, the review count itself certifies completed purchases: it is an action-based signal in Chen et al.'s [3] sense, distinct from the opinion content of the reviews. Studies of review volume find that it is related to sales mainly through an awareness effect rather than through persuasion [16]. Zhu and Zhang [17] further show that online reviews are more influential for less popular products than for popular ones. These findings suggest that OL cues and eWOM content are not substitutes and that their relative weight may depend on the brand.

2.3 The content of eWOM

eWOM content can be classified along several lines. Holbrook [18] distinguishes objective factual information, which describes verifiable physical attributes, from subjective evaluative information, which expresses feelings. Park and Lee [13] distinguish attribute-value reviews—rational, objective and specific, grounded in product attributes and performance—from simple-recommendation reviews, which are emotional, subjective and abstract, expressing feelings without attribute-based argument. Attribute-value content is more diagnostic for high-involvement decisions. Content classifications matter because helpfulness research shows that what makes a review influential is not only its valence but what it is about [19].

For a product sold through an e-commerce store, reviews typically address two objects: the product itself (its authenticity, appearance, function and performance) and the transaction (logistics, delivery speed, customer service, returns). In addition, reviews often reveal for whom the product was bought, which discloses the user segment. Following this logic, we decompose review content into seven dimensions: authenticity, appearance, function and performance, young-user references, older-user references, logistics and customer service. The first three are attribute-value content about the product; logistics and service are attribute-value content about the transaction; the two user-reference dimensions are segment indicators.

2.4 Brand premium and hypotheses

The brand premium of a product—the price it commands above functionally comparable alternatives by virtue of its brand—shapes both the risk a buyer perceives and the cues the buyer needs. For a high-premium product, the dominant risks are that the unit is counterfeit or grey-market and that the premium is not justified by performance; product-centred cues about authenticity and performance are therefore diagnostic, and the brand's own reputation substitutes for information about the seller [20]. For a low-premium product the brand carries less information, counterfeiting is less profitable, and the buyer's residual uncertainty concerns the transaction—whether delivery will be prompt and service responsive—so that service-centred cues become decision-relevant [20]. Brand premium is also likely to select buyers: premium smartphones skew towards younger, fashion-oriented users, mass-market smartphones towards purchases for parents and older relatives. We therefore expect the content of eWOM, and the dimensions that relate to purchase decisions, to differ systematically between the two products.

The foregoing leads to four hypotheses.

H1. Reviews of a high-premium product contain more product-centred content (authenticity, function and performance) and more young-user references, whereas reviews of a low-premium product contain more transaction-centred content (logistics, service) and more older-user references.

H2. Opinion-based eWOM content is positively associated with sales for both products, and function-and-performance content shows the strongest association.

H3. Action-based OL information (review volume) is more weakly associated with sales than opinion-based eWOM content.

H4. Brand premium moderates the decision-relevant dimensions: product-centred dimensions dominate for the high-premium product, whereas transaction-centred dimensions are also decision-relevant for the low-premium product.

3. Research design

3.1 Product and platform selection

Smartphones are conventionally tiered by price: high-end above US\$400 (about RMB 2,669), mid-range between US\$200 and US\$400, and low-end below US\$200. More relevant for our purpose is brand premium. The Apple iPhone X, launched in November 2017, combined a new industrial design, an OLED display, 3D facial recognition and wireless charging with a price several times that of comparable Android devices, and is a paradigmatic high-premium product. The Huawei Honor V9, positioned on value for money with a 5.7-inch display, dual cameras, 4–6 GB of memory, a 4,000 mAh battery and four colour options at a mass-market price, is a low-premium product. Both were sold in the study period through the same official flagship store of Suning.com on Taobao, China's largest consumer e-commerce platform. Holding the store constant removes seller-level differences in logistics and service policy, so that differences in transaction-related review content reflect what buyers of each product chose to write about rather than differences in what they experienced.

3.2 Data collection

Data were collected daily from 1 January to 31 March 2018, yielding 90 daily observations per product. For each product and day we recorded the sales counter displayed on the listing and downloaded all newly posted reviews. To remove noise and manipulation, reviews with no textual content, reviews containing advertising, and reviews whose text duplicated other reviews at a high rate—symptomatic of brushed orders or malicious negative reviews—were removed by item-by-item screening. After screening, 4,806 iPhone X reviews and 1,433 Honor V9 reviews remained for the quarter. Review text was processed with keyword-extraction software to count, for each day, the occurrences of a predefined set of keywords.

3.3 Variables

Table 1. Descriptive statistics of daily observations (N = 90 days per product)

Variable	iPhone X: mean	iPhone X: SD	Honor V9: mean	Honor V9: SD
Sales (units on listing counter)	35,270.68	5,530.20	4,192.10	1,267.67
Authenticity mentions	313.67	202.64	27.68	14.69
Appearance mentions	49.40	34.45	48.26	22.41
Function and performance mentions	273.42	111.21	57.47	31.53
Young-user references	49.27	30.17	2.90	2.10
Older-user references	8.80	8.59	245.21	102.71
Logistics mentions	175.69	178.45	140.64	67.95
Customer service mentions	275.42	178.27	144.21	64.19

Note: Keyword variables are cumulative daily counts of mentions in screened reviews. Source: authors' data, Taobao Suning.com official flagship store, 1 January–31 March 2018.

The dependent variable is sales, measured from the listing's sales counter. The eWOM variables are the daily cumulative counts of keyword mentions in seven content dimensions. Authenticity counts mentions of "genuine" (zhengpin). Appearance counts "good-looking" and "appearance". Function and performance counts "smooth", "pixels", "performance" and related functional terms.

Young-user references count "girlfriend" and "wife", which indicate purchases for or by younger users. Older-user references count "the elderly", "dad", "mum" and their colloquial variants, which indicate purchases for older users. Logistics counts "logistics" and delivery terms. Customer service counts "customer service" and service-attitude terms. The OL variable is the weekly count of posted reviews, which on Taobao certifies the number of buyers who reviewed. Table 1 reports descriptive statistics.

3.4 Analytical approach

The analysis proceeds in four steps. First, we compare the keyword profiles of the two products over the quarter and their weekly evolution, to test H1. Second, we plot weekly sales against weekly review volume for each product to assess whether the OL cue tracks purchase decisions (H3). Third, we compute Pearson correlations between sales and each eWOM dimension for each product using SPSS (H2). Fourth, we estimate an ordinary least squares regression of sales on the seven dimensions for each product to assess which dimensions retain explanatory power when the others are held constant (H4). Because the keyword variables are cumulative counts and sales is a listing counter, both series trend over the quarter; the correlation and regression results should therefore be read as evidence of co-movement over the period rather than as causal estimates, a point we return to in Section 6.

4. Results

4.1 eWOM content profiles of high- and low-premium products

Table 2 compares the total keyword mentions in the two products' reviews over the quarter. The profiles differ sharply and in the direction predicted by H1. iPhone X reviews are preoccupied with authenticity: "genuine" is mentioned 699 times against 46 times for the Honor V9, a ratio of 15:1 even though iPhone X reviews are only 3.4 times as numerous. Performance-related terms ("smooth", "pixels") appear 432 times for the iPhone X and 111 times for the Honor V9, and other functional terms 396 times against 92. Logistics is mentioned 500 times for the iPhone X and 226 times for the Honor V9. Appearance mentions are of similar magnitude for the two products. The user-reference dimensions are mirror images: young-user words dominate iPhone X reviews, where older-user words appear only 13 times in the entire quarter, whereas older-user words dominate Honor V9 reviews, where young-user words appear only 13 times.

Weekly trends sharpen the picture. In iPhone X reviews, authenticity is the most frequently mentioned dimension in every week, reflecting the well-known prevalence of grey-market iPhones and buyers' consequent concern to confirm that the unit is genuine. Appearance mentions and young-user references rise in near-parallel, indicating that young buyers evaluate and comment on the phone's look. Performance mentions are frequent but volatile from week to week, as are logistics mentions. Older-user references are the least frequent dimension throughout. In Honor V9 reviews the ordering is inverted: older-user references are the most frequent dimension in every week; logistics and service mentions are frequent but fluctuate widely; and the four least-mentioned dimensions are performance, appearance, authenticity and young-user references. The scarcity of performance and appearance content indicates that Honor V9 buyers neither expect nor remark on high performance and find the appearance neither disappointing nor striking; the scarcity of authenticity content indicates that buyers trust the store and that counterfeits of domestic mid-range phones are rare. The two products thus attract buyers with different priorities: iPhone X buyers, predominantly young, attend to authenticity, performance and appearance; Honor V9 buyers, predominantly purchasing for older users, attend to price, functionality, delivery and service. H1 is

supported.

Table 2. Total keyword mentions by content dimension, January–March 2018

Content dimension	iPhone X (4,806 reviews)	Honor V9 (1,433 reviews)	Interpretation
Authenticity ("genuine")	699	46	Counterfeit/grey-market risk salient only for the premium brand
Performance ("smooth", "pixels")	432	111	Premium buyers evaluate performance; mass-market buyers expect less
Other functional terms	396	92	As above
Logistics	500	226	Higher absolute count for iPhone X; higher share for Honor V9
Appearance	similar	similar	Appearance mentioned at comparable rates
Older-user references	13	dominant	Honor V9 bought predominantly for parents and older users
Young-user references	dominant	13	iPhone X bought predominantly for or by young users

Note: "Dominant" indicates the most frequent user-reference category for that product; "similar" indicates that appearance mentions are of comparable magnitude for the two products (see Table 1). Source: authors' data.

4.2 Sales and the observational learning cue

Over the quarter iPhone X sales far exceeded Honor V9 sales—the listing counters averaged 35,271 and 4,192 units respectively (Table 1)—consistent with Taobao's predominantly young user base. iPhone X sales fluctuated sharply in early January and late February; Honor V9 sales showed one large movement at the end of March. Comparing weekly sales with weekly review volume, the action-based OL cue, reveals only loose coupling. For the iPhone X, both series rose over the quarter, but when sales jumped between the second and third weeks review volume did not, and when review volume accelerated between the eighth and twelfth weeks sales growth flattened. For the Honor V9, the two series rose in step over most sub-periods, but the sharp increase in review volume between the eleventh and twelfth weeks was not matched by any acceleration in sales, which continued to grow smoothly. Review volume, in other words, moves with sales in the long run—as it must, since reviews are posted by buyers—but week-to-week variation in the number of reviews does not correspond to week-to-week variation in purchase decisions for either product. This is consistent with H3 and with prior evidence that review volume affects sales chiefly through awareness [16].

4.3 Correlations between eWOM content and sales

Table 3 reports Pearson correlations between sales and each of the seven eWOM dimensions. All fourteen coefficients are positive and significant at the 1% level, and all are large, ranging from 0.670 to 0.935. For both products the dimension most strongly correlated with sales is function and performance ($r = 0.935$ for the iPhone X; $r = 0.899$ for the Honor V9), supporting H2: whatever the brand premium, the volume of opinion about what the phone does is the eWOM content that co-moves most closely with purchase decisions. Beyond this common feature, the ordering of dimensions differs between products in ways that anticipate H4. For the iPhone X, customer service

(0.813), authenticity (0.794) and young-user references (0.783) follow function, while logistics (0.670) and older-user references (0.696) are the weakest; young-user references outrank older-user references. For the Honor V9, appearance (0.878), logistics (0.850), older-user references (0.835), service (0.829) and authenticity (0.828) follow function, and young-user references (0.769) are the weakest; older-user references outrank young-user references. The user-reference results confirm that each product's sales move with mentions of its own core user segment. The comparatively low rank of authenticity for the Honor V9 (second lowest) contrasts with its high rank for the iPhone X (third highest), consistent with authenticity being a decision-relevant cue mainly for the premium brand.

Table 3. Pearson correlations between sales and eWOM content dimensions (N = 90)

eWOM content dimension	iPhone X: r	iPhone X: rank	Honor V9: r	Honor V9: rank
Function and performance mentions	0.935**	1	0.899**	1
Customer service mentions	0.813**	2	0.829**	5
Authenticity mentions	0.794**	3	0.828**	6
Young-user references	0.783**	4	0.769**	7
Appearance mentions	0.760**	5	0.878**	2
Older-user references	0.696**	6	0.835**	4
Logistics mentions	0.670**	7	0.850**	3

*Note: ** $p < 0.01$ (two-tailed). Source: authors' data.*

4.4 Regression analysis

Table 4 reports OLS regressions of sales on the seven dimensions entered simultaneously. Both models fit well: R^2 is 0.954 (adjusted 0.949; $F = 239.68$, $p < 0.001$) for the iPhone X and 0.863 (adjusted 0.851; $F = 73.53$, $p < 0.001$) for the Honor V9. The two models differ markedly in which dimensions retain explanatory power. For the iPhone X only two dimensions are significant: function and performance ($B = 70.33$, $t = 6.39$, $p < 0.001$) and young-user references ($B = 259.99$, $t = 3.66$, $p < 0.001$). Authenticity is marginal ($p = 0.069$) and negative, and appearance, older-user references, logistics and service are all insignificant. For the Honor V9 six of the seven dimensions are significant: function and performance ($B = 72.70$, $t = 5.70$, $p < 0.001$), logistics ($B = 43.45$, $t = 3.99$, $p < 0.001$) and customer service ($B = 19.06$, $t = 2.28$, $p = 0.025$) enter positively, while authenticity ($B = -140.66$, $t = -3.71$), appearance ($B = -102.38$, $t = -3.97$) and young-user references ($B = -248.68$, $t = -2.27$) enter negatively; only older-user references are insignificant.

Two features of the regressions warrant comment. First, the contrast between the models supports H4: for the high-premium product, purchase decisions are explained by a narrow set of product-centred cues—performance opinions and the presence of the core young-user segment—and the transaction-centred dimensions add nothing once these are controlled; for the low-premium product, logistics and service retain independent positive explanatory power alongside performance, so that the transaction dimensions of eWOM carry decision-relevant information that product cues alone do not. Second, several standardised coefficients exceed unity in absolute value and several dimensions that correlate positively with sales in Table 3 enter the multivariate models with negative signs. Both are symptoms of strong collinearity among the cumulative keyword series, which move together over the quarter. The negative coefficients on authenticity, appearance and young-user references in the Honor V9 model should therefore not be read as evidence that such content depresses sales; they indicate that, conditional on function, logistics and service content,

these dimensions contribute little independent information. The bivariate patterns in Table 3 and the significant positive effects that are stable across specifications—function for both products, young-user references for the iPhone X, logistics and service for the Honor V9—constitute the robust findings.

Table 4. OLS regressions of sales on eWOM content dimensions (N = 90)

Variable	iPhone X: B (SE)	iPhone X: β	iPhone X: t (p)	Honor V9: B (SE)	Honor V9: β	Honor V9: t (p)
Constant	19,011.05 (543.65)		34.97 (0.000)	1,756.14 (226.32)		7.76 (0.000)
Authenticity	−31.01 (16.86)	−1.136	−1.84 (0.069)	−140.66 (37.87)	−1.630	−3.71 (0.000)
Appearance	−45.91 (79.28)	−0.286	−0.58 (0.564)	−102.38 (25.81)	−1.810	−3.97 (0.000)
Function and performance	70.33 (11.00)	1.414	6.39 (0.000)	72.70 (12.75)	1.808	5.70 (0.000)
Young-user references	259.99 (71.05)	1.418	3.66 (0.000)	−248.68 (109.35)	−0.412	−2.27 (0.026)
Older-user references	−160.15 (122.51)	−0.249	−1.31 (0.195)	−4.27 (3.30)	−0.346	−1.29 (0.200)
Logistics	−11.28 (14.15)	−0.364	−0.80 (0.428)	43.45 (10.84)	2.329	3.99 (0.000)
Customer service	2.20 (5.38)	0.071	0.41 (0.683)	19.06 (8.37)	0.965	2.28 (0.025)
R ² / adjusted R ²	0.954 / 0.949			0.863 / 0.851		
F (df = 7, 82)	239.68 (p < 0.001)			73.53 (p < 0.001)		
Standard error of estimate	1,243.68			489.56		

Note: Dependent variable is sales. B = unstandardised coefficient; β = standardised coefficient.

Source: authors' data.

5. Discussion

5.1 Opinions versus actions

The results bear directly on the distinction between eWOM and OL information. The opinion content of reviews, decomposed by dimension, co-moves closely with sales for both products, whereas the action-based cue of review volume tracks sales only in the long run and not week to week. This does not mean that consumers ignore OL cues—platform sales counters undoubtedly attract attention—but it suggests that in a category like smartphones, where products are high-involvement, information-rich and evaluable on explicit attributes, what other buyers say about the product is more decision-relevant than how many of them have posted. This is consistent with the attribute-value logic of Park and Lee [13] and with the involvement moderation reported by Park et al. [12]. It refines Chen et al. [3] by showing that within opinion-based information, the dimension of opinion matters: it is specifically function-and-performance content that carries the strongest association, for both a premium and a mass-market brand.

5.2 Brand premium and the locus of decision-relevant information

The second contribution is the moderating role of brand premium. For the iPhone X, the brand and the store together resolve uncertainty about the transaction, so that logistics and service content, though present in large volume, add no explanatory power; what remains uncertain, and what buyers look to reviews to resolve, is whether the premium is justified by performance and whether the unit is genuine. Authenticity is the single most mentioned dimension in iPhone X reviews and is strongly correlated with sales, even if it loses significance in the multivariate model to the collinear performance dimension. For the Honor V9 the brand resolves less. Buyers, many of them purchasing for parents, expect adequate rather than outstanding performance, do not worry about counterfeits, and therefore attend to the aspects of the purchase the brand does not guarantee: whether the phone will arrive quickly and whether service will be responsive. Logistics and service content accordingly retain independent explanatory power. The finding parallels Zhu and Zhang [17], who report that reviews matter more for less popular than for popular products, and extends it by identifying which dimensions of review content matter for each.

5.3 Segmentation revealed through eWOM

Third, the user-reference dimensions show that eWOM discloses not only evaluations but the composition of the buyer base. The near-total absence of older-user references from iPhone X reviews and of young-user references from Honor V9 reviews, and the fact that each product's sales co-move with references to its own segment, indicate that the two products serve almost non-overlapping markets despite belonging to the same category and the same store. Young buyers of the premium product care about appearance and performance; buyers for older users care about function, price, delivery and service. Segment composition is thus both a cause and a consequence of the eWOM profile: it shapes what reviewers write about, and what they write about in turn informs the next buyer from the same segment.

6. Conclusions and implications

6.1 Conclusions

Using daily data on a high-premium and a low-premium smartphone sold through the same Taobao store, this paper has examined how eWOM content and OL information relate to customer purchase decisions. Four conclusions follow. First, the two products generate systematically different eWOM: premium-brand reviews are dominated by authenticity, performance and young-user references; mass-market reviews by older-user references, logistics and service. Second, opinion-based eWOM content is strongly associated with sales for both products, and function-and-performance content is the most strongly associated dimension in each case. Third, the action-based OL cue of review volume co-moves with sales only loosely, so that review quantity per se appears to have limited bearing on purchase decisions for either product. Fourth, brand premium moderates which dimensions are decision-relevant: product-centred cues suffice for the premium brand, whereas transaction-centred cues carry additional information for the mass-market brand.

6.2 Implications

For consumers, the results counsel a selective rather than volume-driven use of reviews. In an environment of abundant information and wide choice, buyers should prefer established sellers with a long trading history, compare alternatives, and, when reading reviews, filter for the dimensions

diagnostic of their own uncertainty—authenticity and performance for a premium device, delivery and service for a mass-market one—rather than relying on the number of reviews or the sales counter.

For firms, three implications follow. First, before positioning a smartphone, a firm should establish the brand's standing and the competitive field and identify which user segment the product serves, then analyse that segment's expectations and priorities as revealed in review content, so that product improvement is directed at the dimensions the segment actually evaluates. Second, as smartphone users grow younger and more individualised, brands should recognise the importance of brand-personality associations, offering multi-tiered, differentiated and personalised products, and should build a distinctive brand personality and a clearly defined product feature—as Apple has done with performance, technology and user experience—and reinforce it consistently so that consumers' trust in that feature accumulates. Third, premium brands should attend to the status meaning of their products for educated, high-spending online consumers, for whom a high-end brand signals identity and confers pleasure, confidence and face; mass-market brands, by contrast, should invest in the logistics and service dimensions that their buyers evaluate and reward.

For platforms, the finding that opinion content outperforms volume cues suggests that keyword-level tag statistics and dimension-specific review filters—which Taobao and JD.com have progressively introduced—are more useful to decision-makers than aggregate counters, and that their design should allow buyers of different product tiers to surface the dimensions relevant to them.

6.3 Limitations and future research

The study has limitations that qualify its conclusions and suggest extensions. First, the sales variable is a listing counter and the keyword variables are cumulative counts; both trend over the quarter, so that the large correlation coefficients partly reflect common trend, and the sign reversals and standardised coefficients exceeding unity in the regressions reflect collinearity among the keyword series. Re-estimation on first-differenced or detrended series, with attention to serial correlation and with lagged eWOM terms, is needed before the associations can be interpreted causally. Second, OL information was examined descriptively through weekly review volume; a formal test would require modelling sales against lagged review volume and against the displayed sales counter, ideally exploiting a change in platform display as in Chen et al. [3]. Third, the design compares two products in one store over one quarter, so that brand premium is confounded with brand, launch timing (the iPhone X was two months old) and seasonality around the Spring Festival; a multi-product panel spanning the premium spectrum within and across brands would allow the moderating effect to be identified more cleanly. Fourth, keyword counts capture the salience of a dimension but not its valence; combining dimension classification with sentiment analysis would distinguish, for example, praise of logistics from complaint about it. Finally, the user-reference dimensions are proxies for segment composition inferred from review text; linking review data to buyer demographics would allow the segmentation findings to be validated directly.

Funding

Project No.: 2020J00220, Project Title: Analysis of Cultural Consumption Demand in Countries along the Belt and Road

Project No.: 2019J00012, Project Title: Research on the Influence of Online Word-of-Mouth and Online Observational Learning Information on Customer Decision-Making

References

- [1] Chevalier, J.A., Mayzlin, D., 2006. The effect of word of mouth on sales: online book reviews. *Journal of Marketing Research*, 43(3), 345–354.
- [2] Gu, B., Park, J., Konana, P., 2012. The impact of external word-of-mouth sources on retailer sales of high-involvement products. *Information Systems Research*, 23(1), 182–196.
- [3] Chen, Y., Wang, Q., Xie, J., 2011. Online social interactions: a natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, 48(2), 238–254.
- [4] Hennig-Thurau, T., Gwinner, K.P., Walsh, G., Gremler, D.D., 2004. Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1), 38–52.
- [5] Dellarocas, C., 2003. The digitization of word of mouth: promise and challenges of online feedback mechanisms. *Management Science*, 49(10), 1407–1424.
- [6] Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy*, 100(5), 992–1026.
- [7] Cai, H., Chen, Y., Fang, H., 2009. Observational learning: evidence from a randomized natural field experiment. *American Economic Review*, 99(3), 864–882.
- [8] Arndt, J., 1967. Role of product-related conversations in the diffusion of a new product. *Journal of Marketing Research*, 4(3), 291–295.
- [9] Smith, D., Menon, S., Sivakumar, K., 2005. Online peer and editorial recommendations, trust, and choice in virtual markets. *Journal of Interactive Marketing*, 19(3), 15–37.
- [10] Bickart, B., Schindler, R.M., 2001. Internet forums as influential sources of consumer information. *Journal of Interactive Marketing*, 15(3), 31–40.
- [11] Mizerski, R.W., 1982. An attribution explanation of the disproportionate influence of unfavorable information. *Journal of Consumer Research*, 9(3), 301–310.
- [12] Park, D.-H., Lee, J., Han, I., 2007. The effect of on-line consumer reviews on consumer purchasing intention: the moderating role of involvement. *International Journal of Electronic Commerce*, 11(4), 125–148.
- [13] Park, D.-H., Lee, J., 2008. eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications*, 7(4), 386–398.
- [14] Bandura, A., 1977. *Social Learning Theory*. Prentice-Hall, Englewood Cliffs, NJ.
- [15] Banerjee, A.V., 1992. A simple model of herd behavior. *Quarterly Journal of Economics*, 107(3), 797–817.
- [16] Duan, W., Gu, B., Whinston, A.B., 2008. Do online reviews matter? An empirical investigation of panel data. *Decision Support Systems*, 45(4), 1007–1016.
- [17] Zhu, F., Zhang, X., 2010. Impact of online consumer reviews on sales: the moderating role of product and consumer characteristics. *Journal of Marketing*, 74(2), 133–148.
- [18] Holbrook, M.B., 1978. Beyond attitude structure: toward the informational determinants of attitude. *Journal of Marketing Research*, 15(4), 545–556.
- [19] Mudambi, S.M., Schuff, D., 2010. What makes a helpful online review? A study of customer reviews on Amazon.com. *MIS Quarterly*, 34(1), 185–200.
- [20] Yang, C., Wang, J., 2014. Helpfulness of online product reviews: the moderating role of brand. *Modern Information*, 34(1), 123–127 (in Chinese).