TWO ESSAYS ON PRODUCT POSITIONING AND SOCIAL MEDIA

BY

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DISSERTATION

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ABSTRACT

This dissertation consists of two essays on product positioning and social media. In chapter 1, I study how firms should compete with existing products by enhancing product attributes that are important to consumers. I propose that firms can either improve upon one important attribute significantly (the dominant attribute design strategy) or enhance as many important attributes as possible moderately (the general improvement strategy), given that firms' R&D resources are limited. Results from three empirical studies suggest that when the expected product quality is low or the marketing competition is high, the dominant attribute design strategy is more effective in increasing sales and product evaluations, whereas the general improvement strategy is more effective when the market conditions are the opposite. In chapter 2, I study how online user reviews and online expert reviews jointly affect sales. Although numerous studies have examined their effects separately, their joint effects have been largely neglected. Through three empirical studies, I find that the inconsistency of user reviews and that of expert reviews substitute each other, thus mitigating the negative influences of the inconsistency of user reviews and increasing sales. In addition, product quality could moderate these effects. I also identify the customer breadth effect and the customer depth effect as the underlying mechanisms.

To my wife, my parents, and my parents in law for their love and support.

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CHAPTER 1
TO BE EXCELLENT AT ONE ASPECT OR GOOD AT ALL ASPECTS? : THE EFFECT OF DOMINANT ATTRIBUTE DESIGN ON PRODUCT SALES

Consumers often make choices among alternatives by comparing their performance on important attributes. Attribute-specific positioning and all-in-one positioning are thus two common positioning strategies that firms use to attract consumers by emphasizing the excellent performance of a particular attribute or a combination of multiple important attributes. However, empirical work comparing which strategy is more effective is still rare in spite of the significance and relevance of these strategies. In this study, I consider resource constraints facing firms and examine the relative effectiveness of two close variants of these two strategies. Specifically, I investigate how consumers perceive products that are excellent on one attribute (the dominant attribute design) and their counterparts that are good on all attributes (the general attribute improvement) and how their perception impacts product evaluations and sales under different market conditions. From three studies, I found that when the expected product quality is low, or the marketing competition is high, the dominant attribute design strategy is more effective for increasing sales and product evaluations, whereas in the opposite market conditions, the general attribute improvement strategy is more effective. Limitations and future directions of this study are also discussed.

1.1 INTRODUCTION

Marketers recognized long ago that consumers choose among marketing offerings by comparing their performances on important attributes (Bass and Talarzyk 1972; Bloch 1995; Zhang and Markman 1998). In fact, because product attributes are the most fundamental devices to deliver customer benefits, managers are advised to use attribute design to segment markets (Green and Krieger 1991) and position products (Dröge and Darmon 1987; Steenkamp, Trijp, and Berger 1994).

Two important positioning strategies identified in previous literature are attribute-specific positioning and all-in-one positioning (Chernev 2007; Pham and Muthukrishnan 2002). In an attribute-specific positioning, products are described by a single attribute and the benefits derived from the outstanding performance of the attribute are emphasized in marketing communications. To illustrate, Volvo is positioned as the safest vehicle in the world, and Walmart promises to “save money” for consumers. Such a positioning strategy is largely the contemporary application of the concept *unique selling proposition* (USP hereafter; Reeves 1961). In contrast, all-in-one positioning does not highlight any specific attribute of a product. Instead, firms using this strategy claim or imply that their products are excellent on all attributes and will bring consumers most, if not all, benefits they are looking for. For instance, BMW positions its car to be the “ultimate driving machine,” and Tide detergent makes laundry “simply clean and flesh.” Although many managers, especially those whose products have multiple desirable attributes, face the difficulty of choosing between those two strategies, empirical work has been rare (Pham and Muthukrishnan 2002). In this paper, I aim to examine the effectiveness of these two positioning strategies after considering resource constraints marketers face.

In previous studies, products using the all-in-one strategy are described to be as good as their counterparts applying attribute-specific positioning on all attributes (Chernev 2007). However, in reality, managers often need to trade off the number of attributes to enhance against the degree of improvement of these selected attributes due to resource constraints (e.g., due to the limited budget for R & D expenditure) (Hollins and Pugh 1990). Specifically, as a penny spent on enhancing an attribute often means a penny less available for improving other attributes, it is often the case that products with attribute-specific positioning have better performance on the selected attribute but worse performance on other attributes than do all-in-one products. In this study, I propose two variants of the two above-mentioned positioning strategies that marketers may use to resolve the trade-off between the number and the degree. The first strategy is termed the *dominant attribute design strategy* (hereafter the DAD strategy). That is, by implementing this strategy, firms focus on enhancing one particular attribute and improving it as much as possible (e.g., within the constraint of resources). The second strategy is termed *general attribute improvement strategy* (hereafter the GAI strategy). By implementing this strategy, firms split their resources to generally improve as many important attributes as possible. Due to resource constraints, the resultant products of this GAI strategy are more likely to be mundane than to be outstanding on any attribute. So they largely correspond to the “all-average” products in the extant literature (Nowlis, Kahn, and Dhar 2002; Dhar and Simonson 2003). Note that these two approaches are the two ends of a continuum. At one end, firms emphasize the quality of the improvement (e.g., how much a selected attribute is enhanced), whereas at the other end, firms focus on the quantity of the improvement (e.g., how many attributes are enhanced). In real practice, firms could adopt a mix of the two strategies, with relative emphasis on quality improvement or quantity improvement.

Resultant products from these two strategies are likely to generate different levels of consumer interest. When consumers' idiosyncratic preferences are well defined, selecting among available marketing offerings is a reasonably straightforward process. Previous literature has revealed how consumers make purchase decisions by trading off performance of different attributes and/or comparing attribute performance with predetermined cut-off points (Tversky and Sattath 1979; Kahneman and Tversky 2000). Although different decision-making rules, such as elimination-by-aspect and lexicographical rules, have varying levels of complexity and involve more or fewer steps to narrow down consideration sets, consumers are usually able to make a clear choice eventually. As a result, the sales of a product depend on the size of the group of consumers who find its attribute combination fits their preference better than do other marketing offerings. In a hypothetical scenario, consumers buying a car who care about safety features the most would buy a Volvo model when choosing between Volvo and Toyota due to the excellent performance of the former on safety (thus, Volvo represents a specific attribute positioning). In contrast, those who care about safety, fuel economy, *and* reliability would purchase a Toyota model because Toyota has a reputation of doing well on all three aspects (thus, Toyota demonstrates an all-in-one positioning). The size of each group largely determines how many cars each brand could sell.

However, not all consumers have a well-defined preference. Instead, preference could be constructive in nature and thus subject to the influence of a wide variety of contextual factors, such as relational properties of alternatives in consumers' consideration sets (Payne, Bettman, and Johnson 1991; Simonson 1989). When preference is uncertain, consumers may change the weights of different attributes (Boland, Brucks, and Nielsen 2012; Berger, Meredith, and Wheller 2008), evaluations of attribute performances (Urbany, Bearden, and Weilbaker 1988; Lynch Jr, Chakravarti, and Mitra 1991), and overall evaluations of the focal product dramatically across different situations. For instance, Berger, Meredith, and Wheller (2008) demonstrate that when voters were primed with words such as *education* implicitly by their surroundings (e.g., when the polling booths were set up in a school), they voted in favor of political candidates who supported more investment in education programs. This occurs because voters weighted candidates' standpoints on support of education more heavily when they were in schools than otherwise. In extreme situations, consumers may prefer one option in a two-alternative set in one context but switch to the other due to slight changes in the setting, demonstrating a phenomenon called preference reversal (Tversky, Slovic, and Kahneman 1990). Consequently, relating back to the previous example, at least a subset of consumers may prefer Volvo in one situation but choose Toyota in a different case. The sales and the market shares of each brand, as a result, are also influenced by the choices of consumers in the middle ground who do not have a well-defined preference.

Mainstream theories in marketing make seemingly contradictory predictions about the relative effectiveness of the two strategies in terms of increasing sales. For instance, findings about diminishing sensitivity suggest that consumers become less sensitive and thus attach less value to marginal improvements on an attribute (Tversky and Kahneman 1991). This theory echoes the phenomenon of diminishing marginal utility found in Economics. After a point, most consumers may become satiated with the performance of an attribute, and additional enhancement on that attribute will bring little, if any, increase in utility/evaluations toward the focal product. As a consequence, four units of improvement on an attribute bring less customer value than one unit of improvement on four different attributes. So consumers may form more favorable overall evaluations toward GAI products than DAD products, whether they use the additive or average model when integrating information about multiple attributes to form an overall evaluation (Anderson 1971). However, findings about USP suggest exactly the opposite. This theory implies that firms should position their products and brands in such a way that consumers can clearly associate their brands with an important benefit (Reeves 1961; Kotler and Armstrong 2011). And products perceived to be able to deliver a unique benefit could differentiate themselves from other products in the cluster and generate greater awareness and better sales (Animesh, Viswanathan, and Agarwal 2011). Therefore, USP suggests, albeit implicitly, that DAD products should generate greater sales than GAI products.

In this study, I attempt to investigate the performance implications of the DAD strategy and the GAI strategy in different market environments, with the assumption that at least some consumers do not have a well-established and stable preference. By doing so, I try to help managers make appropriate quality and quantity trade-offs *intentionally*. A caveat of this study, however, is that I confine my analyses to the boundary where all attributes of a product, no matter whether it is a DAD or a GAI product, outperform consumers' minimal requirements. This premise is necessary because when the performance of a product on a particular attribute is extremely low, most consumers would exclude the product from further consideration and the sales could become negligible. In spite of the fact that individual consumers tend to have their own minimum requirements on attributes and that these minimum requirements are unknown to researchers, at the market level a product that has better than average performance on all attributes could safely be assumed to meet the minimum requirements of consumers as a whole on that market (Kivetz, Netzer, and Srinivasan 2005).

To empirically test this research question, I conducted two experimental studies that allowed me to test the possible causality between variables, as well as one secondary data analysis using longitudinal archival data of 146 movies. These studies generated highly consistent results, which can be summarized as follows:

(1) Relative to GAI strategy, DAD strategy has a positive effect on sales and product evaluations when *expected product quality is low* or *market competition is high*; in contrast, DAD has a negative effect when *expected product quality is high* or *market competition is low*, relative to GAI strategy.

(2) *Enhancement of consumer awareness and leverage of perceived risk* mediate the effect of DAD (relative to GAI) on sales and product evaluations.

In the next sections, I first review the related literature, build up my conceptual framework, and develop my hypotheses. Then I report my experimental studies, followed by the secondary data analyses. Finally, I summarize the contributions and managerial implications of this study and discuss its limitations and future research directions.

1.2 LITERATURE REVIEW AND HYPOTHESES

A product is a combination of attributes (Kim and Chhajed 2002). Therefore, attribute design is essentially about setting up attributes so as to deliver greater customer value (Woodruff 1997). It has been well established in previous literature that product designs could at least partly impact product sales by generating positive and/or negative psychological responses on the part of consumers (e.g., Bloch 1995). In the context of this study, based on the nature of the two types of products and relevant findings in the extant literature, I posit that relative to GAI products, DAD products could generate greater consumer awareness and elicit higher perceived risk in the same time.

1.2.1 Product Design and Consumer Awareness

Compared with GAI products, DAD products have excellent performance on a particular attribute but worse performance on other attributes. The outstanding attribute may generate higher consumer awareness for DAD products because, as previous literature shows, individuals tend to pay more attention to unusual, unique, or surprising information (Gershoff, Mukherjee, and Mukhopadhyay 2003). In addition, extremity has been found to be a significant factor in influencing long-term memory (Fiske 1980). Once the performance of that particular attribute becomes extremely positive, consumers are likely to code this piece of information into their long-term memory and thus include the corresponding DAD products into their consideration set when the relevant needs emerge. Therefore, the distinguishingly pleasant performance of DAD products on an important attribute could prompt more attention and potentially provoke more favorable evaluations (Heckler and Childers 1992). Plus, consumers usually act like “cognitive misers”; due to their limited cognitive resources, they do not have the motivation to process information carefully (Fiske and Taylor 2013). So they won’t carefully examine and memorize all detailed information regarding attribute performance (e.g., technological parameters with respect to attribute performance), especially when they are involuntarily exposed to product information. Instead, they may form perceptions such as “the vehicle has the best safety features” and retrieve and use these perceptions as input when they need to make a relevant purchase

(Payne, Bettman, and Johnson 1993). Therefore, DAD products may be more salient and memorable.

DAD products may generate higher consumer awareness as well because of their effects on perceived differentiation. In upgrade settings, Okada (2006) found that participants perceived the new version of a product to be less similar to the old version if the newer one had a few attributes significantly improved, compared with if the new version had all attributes evenly (and less significantly) improved. This greater differentiation is likely to increase customer awareness and thus increase product sales because new products need to be sufficiently different from existing products to compete with them (Kardes and Kalyanaram 1992). More importantly, consumers likely prefer differentiated products, as they can deliver messages about their identity through consumption (Cheema and Kaikati 2010). Therefore, consumer awareness generated by higher perceived differentiation is likely to benefit product sales.

1.2.2 Attribute Design and Perceived Risk

However, the DAD strategy can also generate negative reactions from consumers. In particular, Srinivasan and Ratchford (1991) found that unfamiliarity increases perceived risk. Consumers may therefore consider a DAD product riskier relative to a GAI product because the outstanding performance of its dominant attribute is usually less common and probably more extreme than that of the corresponding attribute of a majority of products on the market. In fact, consumers may perceive higher product uncertainties from products that are very different from the market average (Marks and Kamins 1988).

Research on extremeness avoidance also suggests that consumers may perceive higher risk from a DAD product. Specifically, when considering among three alternatives, namely, two extreme options that have either a strong attribute 1 or 2 and a middle option whose performance on both attributes is in the middle, consumers may perceive higher risk from extreme options and thus are more likely to select the middle option, especially when they are expected to justify their choices later on (Simonson 1989; Simonson and Tversky 1992). In a different study, Mourali, Böckenholt, and Laroche (2007) found direct evidence that because extreme options are associated with greater risk, prevention-focused consumers tend to avoid them more than do promotion-focused consumers. What is more, a DAD product usually has larger dispersion in attribute performance than a GAI product does. As a result, consumers may perceive it to be more unbalanced and as a result, associate it with higher risk. Chernev (2005) suggests that when firms use aggregate attributes, such as reliability and ease of use, to describe their offerings and when they use numerical ratings to illustrate the performance of a product on aggregate attributes, consumers can easily recognize whether a product has balanced performance or not. An option whose performance ratings on two attributes is (70, 70) is perceived to be less extreme than a counterpart whose ratings are (60, 80); the former option is thus more likely to be selected. In these classical demonstrations of compromise effect, the extreme options are analogous to a DAD product and the middle option is very similar to a GAI design. So findings about compromise effect may apply to the comparison between a DAD and a GAI product and suggest the former to be associated with higher risk.

Previous studies have demonstrated that the relationship between product attributes and product sales could be moderated by a variety of factors (e.g., Gourville and Soman 2005; Lam et al. 2010). In this study, I consider competition intensity and expected product quality as possible moderators because I posit that they are able to either amplify or suppress the two mechanisms, namely, enhancement of consumer awareness and leverage of perceived risk, discussed above. As a consequence, these factors could determine whether a DAD product or a GAI product will generate better sales. In addition, these two factors have been considered by many previous studies and are generally believed to be significantly relevant and important in determining firms' performance.

1.2.3 The Moderating Role of Competition Intensity

Competition intensity captures the number of alternative choices in the same market—the more alternative products there are in the same market, the higher the competition intensity (Gu, Hung, and Tse 2008; Roberts 1999). When the competition intensity increases, consumers face a broader variety of choices and it becomes harder for a product to catch their awareness. In particular, more alternatives increase the competitive interference, or "clutter," in the marketplace; consequently, firms desperately need unique methods to catch consumer attention. Competitive interference arises from marketing activities that are delivered simultaneously by competing companies in the industry (Danaher, Bonfrer, and Dhar 2008). Such interference cancels each company's marketing effort out and makes it hard for a marketing offering to stand out. As a result, consumer awareness generated by a product itself (e.g., the attribute performance of a product) is more valuable and stronger in a high competitive market than in a low competitive market. What is more, when facing a large number of choices, consumers usually simplify their choices by using salient cues to justify their choices (Sela, Berger, and Liu 2009). In this case, for a company being able to differentiate its product from competing ones is more beneficial. In other words, consumers are more likely to use their general impressions, such as, "This HDTV has the best picture quality," to form consideration sets and conduct their initial screening on available options. In fact, Payne, Bettman, and Johnson (1993) suggest that, as the number of alternatives increases, consumers are more likely to use attribute-based heuristics, such as lexicographic and elimination-by-aspect rules, to make choices. So alternatives without outstanding and clear selling points are more likely to be ignored when the competition intensity is high than when it is low. In sum, the differentiation benefit of a DAD product could be stronger when there are a large number of competing products on the market than otherwise.

Furthermore, competition intensity may also influence perceived risk. When competition is high, firms usually have to work on improving the quality of their products and increasing consumer satisfaction in order to survive the fierce competition. On the contrary, when competition is low, so firms could act like a monopoly or an oligopoly, quality usually suffers (Banker, Khosla, and Sinha 1998). Consumers may notice the positive relationship between quality and competition intensity on the basis of their prior purchase experience and form a sort of lay theory in their minds. When applicable, these lay theories may be applied and thus impact consumers' judgments (Mukhopadhyay and Yeung 2010). Therefore, the perceived risk derived from the unbalanced attributes of DAD products may be at least partly mitigated when competition intensity is high, compared with when it is low, since in the former case firms need to compete harder on earning customer satisfaction and are more likely to ensure a focal product to deliver the benefit it is supposed to do. So even if a product has unbalanced attributes, it has less chance of failing its promises when competition intensity is high than otherwise. Therefore, I predict that:

Hypothesis 1: Competition intensity positively moderates the effects of attribute design on product sales, such that when the competition intensity is high, a DAD strategy leads to greater sales than does a GAI strategy. However, when competition intensity is low, the opposite is true.

1.2.4 The Moderating Role of Expected Product Quality

Consumers' expectation plays a big role in determining information retrieval, judgments, and choices (Helgeson and Beatty 1987; Oliver and DeSarbo 1988). Once an expectation is in place, information about a product will be compared with expectations by consumers, and the direction of the discrepancy largely determines whether consumers will be satisfied with the focal product or not. As price is a salient cue for judging product quality (Aaker 1991; Wolinsky 1983), many consumers form initial quality expectation on the basis of price. Additionally, when they start searching the market, they usually have a budget allocated to a particular purchase, so they know they could expect low or high quality from products in their consideration sets.

When consumers have a low quality expectation toward potential products, they would expect the attribute performance to be low as well. Consequently, the superior performance of a DAD product on an attribute would appear even more novel and surprising than if consumers have a high quality expectation. Such a surprise is likely to generate positive mood and result in increased consumer awareness (Lee and Sternthal 1999; Heckler and Childers 1992), so a DAD product, relatively to a GAI product, may draw more attention and generate more awareness from consumers when expected product quality is low. However, the differentiation benefits brought by a DAD design are more likely to be recognized by potential consumers when the expected product quality is high than when it is low because product differentiation is more meaningful when expected product quality is high. So expected product quality may elicit two contradictory influences on consumer awareness.

The effect of the DAD design on perceived risk is also likely to be moderated by expected product quality. West and Broniarczyk (1998) demonstrate that when the product quality is higher than their aspiration levels, consumers prefer products which are less risky. In contrast, they prefer riskier products when the expected product quality is lower. This suggests that consumers are more sensitive to and less tolerate of potential risks when expected product quality is high than when it is low. Therefore, a DAD product may elicit greater perceived risk when the focal product is expected to be of high quality than otherwise.

In sum, a DAD product, compared with a GAI product, could elicit two opposite effects on consumer awareness. On the one hand, its attribute combination contributes to increased consumer awareness when the product is expected to have low quality than otherwise. On the other hand, it may decrease consumer awareness because consumers won't appreciate the differentiation from a product expected to be of low quality. In addition, a DAD product could also lead to decreased sales by amplifying perceived risk when expected product quality is high. Given these opposing mechanisms, and that there is no evidence to suggest which mechanism(s) is stronger, I provide the following alternative hypothesis:

Hypothesis 2a: Expected product quality positively moderates the effects of attribute design on product sales, such that when the product is of high quality, a DAD strategy leads to greater sales than does a GAI strategy. However, the opposite is true when the product is of low quality.

Hypothesis 2b: Expected product quality negatively moderates the effects of attribute design on product sales, such that when the product is of high quality, a DAD strategy leads to lower sales than does a GAI strategy. However, the opposite is true when the product is of low quality.

1.3 STUDY 1

Study 1 aims to test the moderating role of competition intensity on the effect of the DAD and the GAI designs on product evaluations. According to my conceptualization, when consumers have many options to choose from, they will evaluate a DAD product better than a GAI product mainly because 1) they need to simplify their decision strategies to minimize their cognitive effort and 2) the unusually excellent performance of the DAD on an attribute is likely to draw more of their attention when consumers need to select from a large assortment rather than from a small one. On the contrary, when consumers have a very small number of options to select from, they will evaluate a GAI product as being better.

A total of 328 participants recruited from a national panel took part in this 15-minute study for a small monetary reward. They were randomly assigned to one condition of a 2 (competition intensity: high vs. low) × 4 (attribute design: three DAD conditions vs. one GAI condition) between-subject factorial design. Note that despite the fact that this study had different numbers of DAD and GAI conditions (3 vs. 1), it was designed in a way that participants had an equal chance to be assigned to either a DAD condition or a GAI condition. Participants' average age is 32.7, and 53% of them are males.

1.3.1 Procedures and Measures

This study was conducted on computers. The instructions informed participants that this study was aimed at finding out how to make online review information easier for potential consumers to use. Under this pretense, participants read information about several digital cameras. In the high competition intensity condition, information about attribute performance of seven different camera models was presented, whereas in the low competition intensity condition, information about three models was provided. The first three models in the two conditions were exactly the same (see Figure 1 in the Appendix). These cameras differed on three attributes, namely, imagine quality, widest angle, and battery life. Participants were told that their minimal requirements on these attributes were all 60 out of 100, so they should imagine that they were seriously choosing among them, given that all the options had the potential to fit their preferences. To control the possible differences on attribute importance, the three attributes were selected to be the dominant attribute alternately in the three DAD conditions. For instance, when image quality was the dominant attribute, the focal product was said to have a rating of 90 out of 100 on image quality and 75 out of 100 on widest angle and battery life. In contrast, the focal product was said to have ratings of 80 out of 100 on all three attributes in the GAI condition. In all conditions, participants were informed that they only needed to evaluate one alternative that would be randomly assigned to them. In fact, all participants were asked to evaluate option B in the set, which was either a DAD product or a GAI product, depending on the condition. After evaluating option B, participants responded to questions measuring perceived attribute performance and perceived competition intensity and then reported their demographics, such as age and gender. Next, participants answered questions about whether the review information was clear enough to potential buyers (such data were not analyzed). At the end, participants were asked to report what they thought was the real purpose of this study. None of them successfully guessed the hypothesis of this study.

1.3.2 Measures

Three 7-point scales were employed to measure participants' overall evaluations of the digital camera. They were "How favorable do you think option B is" (1 = "not favorable all" and 7 = "very favorable"), "How much do you like option B?" (1 = "do not like it at all" and 7 = "like it very much"), and "How good do you think option B is?" (1 = "not good at all" and 7 = "very good"). Three questions—"How good is the image quality/widest angle/battery life?" —were used to measure participants' evaluations of each attribute from 1 (not good at all) to 7 (very good). In addition, one item—"How intense do you think the competition that model B is facing"—was used to measure competition intensity.

1.3.3 Results

Manipulation checks. Participants did feel that model B faced fiercer competition when competition was high (M = 5.24) than when it was low (M = 4.80), t (326) = 3.15, p < .01, suggesting the manipulation of competition intensity was successful. In addition, participants in the condition where image quality was a DAD attribute rated the image quality (M = 5.92) better than the corresponding attribute in the GAI condition (M = 4.43), t (326) = 15.28, p < .001. Similar results hold for the other two conditions, in which widest angle or battery life was a DAD attribute, respectively, all p < .01.

Product evaluations. A single index was created by averaging the three items measuring product evaluations (α = 0.94). Then it was analyzed as a function of attribute design and competition intensity. See Figure 1.1 for the comparison of cell means. As expected, the two-way interaction was significant, F (1, 324) = 40.68, p < .001. Further analyses showed that when the competition intensity was high, participants evaluated the product more favorably if it was a DAD design than if it was a GAI design (M = 5.45 vs. M = 4.85), F (1, 324) = 9.89, p < .01. The opposite was true when the competition intensity was low (M = 4.61 vs. M = 5.72), F (1, 324) = 34.85, p < .001. Neither of the two main effects was significant, both p > .20.

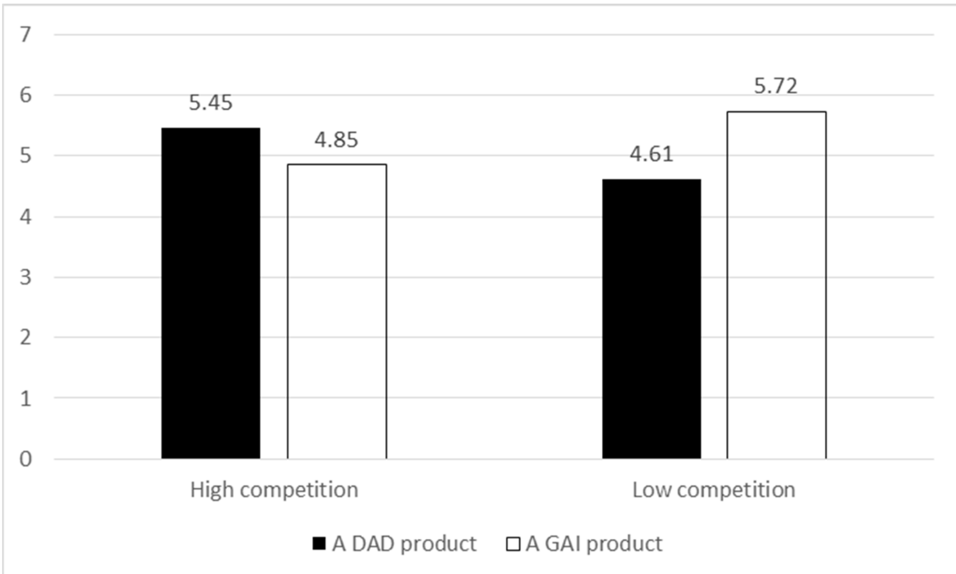

Figure 1.1 The ANOVA results of Study 1

1.4 STUDY 2

The purposes of Study 2 are twofold. First, Study 1, in spite of providing causal evidence of the moderating role of competition intensity on the effect of DAD design, does not examine the proposed mechanisms of how DAD versus GAI design impacts product evaluations. Study 2 will fill in this gap. Specifically, in Study 2, I test the total mediating effect of the two mechanisms, namely, consumer awareness and perceived risk. Second, Study 2 aims to test the moderating role of expected product quality. In this study, expected product quality is manipulated by brand name. Previous research (Keller 1993; Aaker 1997) shows that consumers associate brand names with different levels of benefits, quality, and prestige. Therefore, consumers may have completely different expectations of the quality of products by two brand names. In this study we use two brand names, Sony vs. Pandigital, one well known and one almost unknown, to manipulate consumers' expectation on product quality. A total of 300 participants recruited from the same national panel as in Study 1 took part in this 15-minute study for a small monetary reward. They were randomly assigned to one condition of a 2 (expected product quality: high vs. low) × 5 (attribute design: four DAD conditions vs. one GAI condition) between-subject factorial design. The focal product is a digital picture frame which has four important attributes, namely ease of use, viewing angle, picture quality, and versatility. Although this study had four DAD conditions and one GAI condition, it was designed in such a way that participants had an equal chance to be assigned to either the DAD condition or the GAI condition. Their average age was 33.8, and 48% of them were males. This study was run under the same cover story as in Study 1 and the data bout review clarify were not analyzed.

1.4.1 Procedures and Measures

Procedures and measure used in Study 2 were generally the same as in Study 1. One exception was that the manipulation of competition intensity was replaced by the manipulation of expected product quality. As mentioned before, product quality was manipulated by the brand names. In the high (low) brand reputation condition, participants were told that they were seriously considering a digital picture frame by Sony (Pandigital). DAD versus GAI was manipulated in the same way as in Study 1 by numerical ratings. In addition, all participants were informed of the market baselines on all four attributes.

Two 7-point items—"How much do you think this product can draw prospective consumers' attention?" (1 = "Very little" and 7 = "Very much") and "How similar do you think this product is to other alternatives on the market?" (1 = "Not at all" and 7 = "Very much," reverse-coded)—were used to measure consumer awareness. Two other items, namely, "How uncertain do you feel the performance of this product is?" (1 = "Not uncertain at all" and 7 = "Very uncertain") and "How risky do you feel purchasing this product is?" (1 = "Not risky at all" and 7 = "Very risky"), were used to measure perceived risk. And two 7-point items—"How much do you like the brand, Sony/Pandigital?" (1 = "very little" and 7 = "very much") and "How favorable do you think the brand, Sony/Pandigital, is?" (1 = "not favorable at all" and 7 = "very favorable")—were added to measure the brand reputation. All six of these items were listed after the measure of product evaluations but before questions about demographic variables. Items measuring product evaluations and attribute performance were the same as in Study 1 with necessary modifications.

1.4.2 Results

Manipulation checks. Two items measuring perceived brand reputation were averaged to form a composite index (r = .89, p < .001). The result of a t-test showed that participants rated Sony to be much more favorable (M = 5.57) than Pandigital (M = 3.90), t (298) = 10.97, p < .001. The manipulation of attribute design was successful as well. For instance, if the brand name was Sony, participants in the condition where viewing angle was a DAD attribute rated the performance of the focal product on this attribute (M = 6.50) better than that of the corresponding GAI condition ($M = 5.31$), $t(89) = 3.57$, $p < .001$. Similar results hold for the other comparisons, in which the dominant attribute was ease of use, picture quality, or versatility, respectively, all $p < .01$. In the analyses below, the four DAD conditions were collapsed because no significant differences on the dependent variable were found among them.

Product evaluations. A single index was created by averaging the three items measuring product evaluations ($\alpha = 0.83$). Then it was analyzed as a function of attribute design and expected product quality (Sony vs. Pandigital). See Figure 1.2 for the comparisons between cell means. As expected, the two-way interaction was significant, $F(1, 296) = 24.54$, $p < .001$. Further analyses showed when the brand name was Sony and therefore expected product quality was high, participants evaluated the product more favorably if it was a GAI design than if it was a DAD design ($M = 5.52$ vs. $M = 4.84$), $F(1, 296) = 20.02$, $p < .001$. The opposite was true when the brand name was Pandigital ($M = 4.87$ vs. $M = 5.27$), $F(1, 296) = 6.56$, $p < .02$. Neither the main effect of expected product quality nor that of attribute design was significant. The absence of the main effect of expected product quality (Sony vs. Pandigital) was unexpected because other data did show that participants liked the brand name Sony much better than Pandigital. In spite of the fact that participants evaluated a focal product made by Sony better than a counterpart by Pandigital, the difference was too small to achieve significance ($M = 5.21$ vs. $M = 5.07$). We posit that this occurs probably because participants counted more heavily on numerical ratings of all important attributes when making evaluations, resulting in a dilution of the effects of brand names on product evaluations.

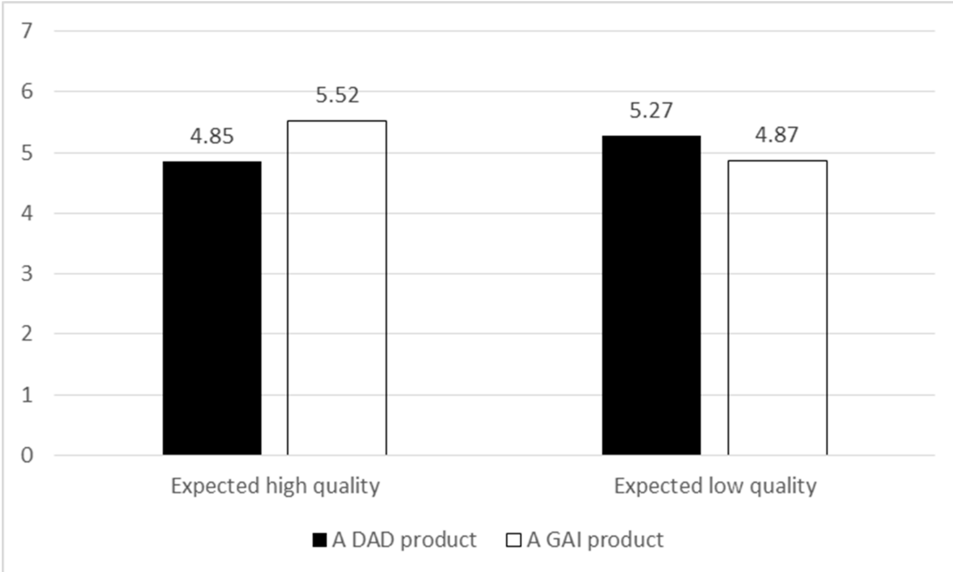

Figure 1.2 The ANOVA results of Study 2

Mediated moderation. I tested the mediating roles of consumer awareness and perceived risk in explaining the interactive effect of attribute design and expected product quality on product evaluations. The two items measuring consumer awareness and the other two measuring perceived risk are highly correlated (r = .62 and r = .66, respectively, both p < .01), so two composite indexes were created by averaging the responses on corresponding items. In addition, because in our conceptualization consumer awareness is a positive mediator but perceived risk is a negative one, we minus perceived risk from consumer awareness and use this resultant index as the mediator in the mediated moderation analysis below.

Following Hayes (2013), two regression models were used to assess the indirect effects. The mediator model is: $M_e = \alpha_0 + \alpha_1 \times X + \alpha_2 \times M_o + \alpha_3 \times X \times M_o + r$ and the dependent variable model is: $Y = b_0 + c_1' \times X + c_2' \times M_o + c_3' \times X \times M_o + b_1 \times M_e + r$, where M_e is the mediator (i.e., the net effect of consumer awareness and perceived risk), X is the independent variable (i.e., attribute design: DAD vs. GAI), M_o is the moderator (i.e., expected product quality: high vs. low), and Y is product evaluations.

In the mediator model, the interactive effect of attribute design and expected product quality on the net effect of consumer awareness and perceived risk was significant (α_3 =1.38, SE =.29, t = 4.80, p < .001). In the dependent variable model, the net effect of consumer awareness and perceived risk was significant (b_1= .28, SE =.04, t = 6.75, p < .001), whereas the direct interactive effect of attribute design and expected product quality on evaluations became less significant (c_3' = .70, SE =.21, t = 3.30, p < .01). Bootstrap tests showed that the interactive effect of attribute design and expected product quality on evaluations was mediated by the net effect of consumer awareness and perceived risk (95% Bias Corrected Confidence-Interval using 5000 bootstrap samples: .19 to .66). Thus, this experiment provided evidence for the mediating effects of consumer awareness and perceived risk.

1.5 STUDY 3

1.5.1 Research Context

In Study 3, I examine whether my conceptualization could be generalized to other settings and whether my findings still hold if I use real sales data as the main dependent variable, instead of the product evaluations in Study 1 and Study 2. So in this study I test my hypotheses using secondary data collected from the U.S. movie industry. I chose the U.S. movie industry as the research context for several reasons. First, movie attributes, such as direction and action, are important factors influencing movie-going behaviors (Gershoff et al. 2008), and performances of movie attributes are easily accessible on many websites, such as Yahoo!Movies. As did Tellis and

Johnson (2007), I use average ratings of individual attributes as the indicators of a movie's performance on corresponding attributes. Second, the prices of movies are relatively stable and consistent, so I can control the effect of price and a wide variety of promotions found in other industries. Finally, when developing movies, managers seem to focus on different strategies, which largely correspond to the DAD and GAI strategies proposed by this study. For example, *The Last Airbender* seemed to use dominant attribute design that emphasizes movie visuals, as it got outstanding average ratings from moviegoers, while movies such as *Morning Glory* and *Leap Year* appear to emphasize every movie attribute. Each year around 200 new movies are released in the U.S. market. The large number and wide differences in terms of attribute combination provide an ideal context for my research purpose. My data set contains data collected from a variety of secondary sources about 146 movies released between December 2009 and December 2010.

1.5.2 Measurement and Data Sources

Dependent variable. I use *product sales* as my dependent variable. Consistent with Dellarocas, Zhang, and Awad (2007), I obtained weekly box office data from the Box Office Mojo website and used it as the dependent variable. Specifically, box office performance of a movie in the first four weeks appeared in my model as the dependent variable because box office revenues in the first four weeks account for about 90% of each movie's total box office revenues.

Dominant attribute design (DAD) versus general attribute improvement (GAI). In order to measure DAD versus GAI products, I need to consider several issues. First, I need information about movies regarding their performance on each attribute. In this study, I focus on "subjective" attribute performance based on consumer ratings. In particular, I collected data of movie attribute ratings from Yahoo!Movies (Chintagunta, Gopinath, and Venkataraman 2010; Moon, Bergey, and Iacobucci 2010). Moviegoers can post online movie reviews on Yahoo! and rate a movie's overall performance and its four attributes, respectively—*story, action, direction,* and *visual*—on a scale from F to A+. These alphabet ratings were converted to numeric ratings ranging from 1 (F) to 13 (A+). For the performance of each movie attribute, I used the average of cumulative ratings from the opening week to one week before the weekly sales were measured (Moe and Trusov 2011) because all prior reviews affect the decisions of future moviegoers (Moon et al. 2010) and the one-week time lag helps us to rule out the reverse causality inferences that the box office performance influences the evaluations of attribute performance.

Second, my measure of attribute performance is in comparison with average performance of all movies in the market, as noted in the caveat discussed before. Therefore, for each attribute, I calculate a specific movie's attribute performance as the difference between its own performance on each attribute and the average corresponding performance of all movies available in that week. In this sense, attribute performance is a time-changing variable; its own and other available movies' attribute performance may change over time because new reviews come in every week and the available movies in the market also change week by week. More importantly, since product improvement means that the attribute performance of a product needs to be better than the market baseline, the rating of an enhanced attribute should be greater than the market average. So based on the relative attribute performance calculated above, I only include movies whose average ratings on all four attributes were greater than market average into the data set I eventually use.

Third, these attributes may not be equally important, so I need to control for the relative importance of each movie. Therefore, I calculate importance-weighted attribute performance. To control for the relative weights consumers place on each attribute in forming their overall evaluation of a movie, I first run the following regression at review level to detect attribute importance (Tellis and Johnson 2007):

(1) Overall $\text{Rating}_j = \alpha_0 + \beta_s \times \text{StoryRating}_j + \beta_a \times \text{ActionRating}_j + \beta_d \times \text{DirectionRating}_j + \beta_v \times \text{VisualRating}_j + \varepsilon_j$

The overall rating at the individual review level is also obtained from Yahoo!Movies, which measured consumers' *overall* evaluation of movies on a scale from F to A+. Following Tellis and Johnson (2007), $\beta_s/(\beta_s+\beta_a+\beta_d+\beta_v)$ is used as importance weight for story attribute. Similarly, $\beta_a/(\beta_s+\beta_a+\beta_d+\beta_v)$, $\beta_d/(\beta_s+\beta_a+\beta_d+\beta_v)$, and $\beta_v/(\beta_s+\beta_a+\beta_d+\beta_v)$ are the importance weights for action, direction, and visual, respectively.

After I calculate importance-weighted attribute performance across all four attributes, I obtain attribute performance from the best-performing attribute as the dominant attribute and subtract the average performance across these four attributes (which would be the attribute performance for GAI). In this way, I capture the relative effect of DAD as compared with GAI. See the equation below to find out how I do the calculation.

$$DAD_i = \max_t \left\{ \omega_t \left(x_{it} - \frac{\sum_{i=1}^{N} x_{it}}{N} \right) - \frac{\sum_{t=1}^{T} \omega_t \left(x_{it} - \frac{\sum_{i=1}^{N} x_{it}}{N} \right)}{T} \right\}$$

ω_t = the importance of attribute t

$x\_i\,t$ = the rating of movie i at attribute t

T = 4, the number of attributes

N = the number of movies

Competitive intensity. Following Fang, Palmatier, and Grewal (2011), I measured market competition as a variant of the Herfindahl-Hirschman Index on the basis of the number of screen spaces, which captures the strength of competition for screen space. I collected the weekly number of screens occupied by each movie from Box Office Mojo.

(2) Competitive intensity$_t$= 1-$\sum_i$Share$_{i,t}^2$= 1-$\sum_i$(Screen$_{i,t}$/$\sum_i$(Screen$_{i,t}$))^2,

where Share$_{i,t}$ is the ratio of the number of screens occupied by movie i (Screen$_{i,t}$) to the total number of screens in the market at week t ($\sum_i$(Screen$_{i,t}$)).

Expected product quality. Product cost is used as a proxy of expected product quality. Big-cost movies likely involve powerful stars, lavish sets and costumes, expensive digital manipulations, and special effects (Basuroy, Chatterjee, and Ravid 2003). Therefore, movie cost largely signals the quality of a movie (Litman and Ahn 1998), and consumers usually expect a high-budget movie to be of high quality. I also coded movie quality as a time-changing variable for several reasons, as consumers tend to form expectations on the basis of comparisons rather than absolute judgments (Tversky and Kahneman 1991). So, first, the market baseline is measured as the average of cost expenditures for all movies in my sample at week t; second, for movie i at week t, the movie's relative quality is calculated as the difference between its cost and the market baseline. The movie cost data were collected from Box Office Mojo and IMDb websites.

Control variables. I also add several control variables because of their potential influence on the dependent variable. First, I need to control for the overall attribute performance. In particular, the overall performance is measured as the average of overall ratings from the opening week to one week before the corresponding weekly sales were measured (Moon et al. 2010). In addition, I also controlled for the volume and variance of customer reviews. Volume represents the cumulative number of movie reviews (Liu 2006; Moon et al. 2010), and variance is measured as the standard deviation of the overall ratings (Moe and Trusov 2011), from the opening week to one week before the corresponding weekly sales were measured. Furthermore, I used a *week* variable to denote the number of weeks since the movie's release to the week in which I measured the dependent variable (Basuroy, Desai, and Talukdar 2006). And the *screen* control variable measured the number of screens on which the movie was playing in the week when I measured the dependent variable (Liu 2006; Elberse and Eliashberg 2003). Also, I included box office revenue of the prior week to control for state dependence (Moon et al. 2010). The above control variables data were also obtained from Box Office Mojo.

In sum, my data set consisted of 589 observations for 148 movies over four-week time periods. After screening out the observations for which at least one of four average ratings on four attributes were less than the market average, I obtained a final data set containing 255 observations for 69 movies.

1.5.3 Model Setup

There are several issues that I need to cope with when estimating the model: (1) reverse causality between attribute performance and product sales, (2) the panel data structure, (3) the normality and homoscedasticity of product sales, as well as (4) multicollinearity. I address each concern in the steps listed below.

First, I created a one-week time lag between independent variables and product sales to rule out the potential of reverse causality (Boulding and Staelin 1995). Second, I then tested unobserved, fixed movie-specific effects using the Hausman test. The chi-square statistic was significant ($\chi^2 = 101.60$, $p < .00$). To eliminate the influence of unobserved fixed effects, I followed prior studies by using first-differencing approach (Boulding and Staelin 1995;

Steenkamp and Fang 2011). Third, I tested whether the normality, homoscedasticity, and multicollinearity should be a concern to us. For normality, I checked product sales with skewness and kurtosis. Since box office data is right-skewed, we took the log-transformation of weekly box office revenues (Elberse and Eliashberg 2003). I screened for homoscedasticity using a standardized scatter plot of the predicted dependent variable by the standardized residuals. The residuals were randomly scattered around 0 and provided a relatively even distribution, such that homoscedasticity of the variance of errors is a valid assumption for these data. Furthermore, I assessed multivariate multicollinearity by examining the variance inflation factor (VIF). The VIF values ranged from 1.132 to 7.642, indicating that multicollinearity is not a serious issue.

Following prior studies (Chevalier and Mayzlin 2006; Steenkamp and Fang 2011; Zhu and Zhang 2010), I estimated the following first-difference model:

$$
\begin{aligned}
(3)\ & \text{Log (Box Office}_{i,t}) - \text{Log (Box Office}_{i,t-1}) \\
& = \beta_1(\text{DAD}_{i,t-1} - \text{DAD}_{i,t-2}) \\
& + \beta_2(\text{DAD}_{i,t-1} \times \text{Competitive Intensity}_t - \text{DAD}_{i,t-2} \times \text{Competition Intensity}_{t-1}) \\
& + \beta_3(\text{DAD}_{i,t-1} \times \text{Quality}_{i,t-1} - \text{DAD}_{i,t-2} \times \text{Quality}_{i,t-2}) \\
& + \beta_4(\text{DAD}_{i,t-1} \times \text{Product Type}_i - \text{DAD}_{i,t-2} \times \text{Product Type}_i) \\
& + \beta_5(\text{Competition Intensity}_t - \text{Competition Intensity}_{t-1}) + \beta_6(\text{Quality}_{i,t-1} - \text{Quality}_{i,t-2}) \\
& + \beta_7(\text{Overall Attribute Performance}_{i,t-1} - \text{Overall Attribute Performance}_{i,t-2}) \\
& + \beta_8(\text{Volume}_{i,t-1} - \text{Volume}_{i,t-2}) + \beta_9(\text{Variance}_{i,t-1} - \text{Variance}_{i,t-2}) \\
& + \beta_{10}(\log(\text{Week}_{i,t}) - \log(\text{Week}_{i,t-1})) + \beta_{11}(\log(\text{Screen}_{i,t}) - \log(\text{Screen}_{i,t-1})) \\
& + \beta_{12}(\log(\text{Box Office}_{i,t-1}) - \log(\text{Box Office}_{i,t-2})) + (\mu_{i,t} - \mu_{i,t-1}),
\end{aligned}
$$

where DAD is the relative effect of DAD versus GAI. Note that after first-differencing, the time constant variable does not appear in the model anymore.

1.5.4 Estimation Results

Following Aiken and West (1991), I mean-centered the DAD variable and moderators before I created the interaction terms. When estimating the first-differencing model, I used stepwise analysis and first included all independent and control variables, then added the two interaction terms. The results are reported in Table 1.1. To examine interaction effects in detail, I conducted simple slope analyses, such that I avoided the need to create subgroups from continuous independent variables (Aiken and West 1991; Fang 2008). Specifically, I split the moderators into high (two standard deviations above the mean) and low (two standard deviations below the mean) groups and estimated whether the effect of DAD design on movie box office revenues differs between them. Refer to Table 1.2 to see the simple slope analyses.

Regarding the effects of the control variables, the results are very consistent with findings in prior studies. While the valence and variance of overall ratings increase sales (Chintagunta et al. 2010), the amount of screens increases the revenues too (Elberse and Eliashberg 2003). Furthermore, box office decreases over time (Basuroy, Desai, and Talukdar 2006), and a higher box office in the prior week positively affects the current week's box office (Moon et al. 2010). These results further provide face validity for the estimation results.

The main effect of DAD is not significant. But Tables 1.1 and 1.2 indicate that a DAD attribute can be a double-edged sword; in other words, it can either hurt or help box office, depending on competition intensity and expected movie quality. Specifically, Table 1 shows that the interaction effect between *DAD* and *Competition* on box office is positive ($\beta = 26.165$, $p < .01$; H1 supported) and that the interaction effect between *DAD* and *Quality* on box office is negative ($\beta = -.347$, $p < .01$; H2b supported).

Table 1.1 The Effects of DAD on movie box office

		Model 1		Model 2	
		Coef.	**S.E.**	**Coef.**	**S.E.**
Main Effects					
D_DAD		0.479	0.085***	0.212	0.303
D_Competition		-3.135	4.554	-4.525	3.559
D_Quality		0.040	0.043	0.054	0.082
Moderating Effects					
D_DAD × Competition	H1 supported			26.165	4.314***
D_DAD × Product quality	H2b supported			-0.347	0.055***
Control Variables					
D_Overall Performance		0.173	0.034***	0.192	0.041***
D_Volume		0.0002	0.0001*	0.0002	0.0001*
D_Variance		0.088	0.077	0.110	0.096
D_Log (Screens)		0.741	0.049***	0.738	0.048***
D_Log (Week)		-0.886	0.094***	-0.905	0.108***
D_Log (Box Office)		0.143	0.002***	0.131	0.006***
R^2		0.606		0.627	
Incremental R^2 test *F*-value				0.21*	

**p*< .05; ***p*< .01; ****p*< .001

Note: DAD is the relative effect of DAD vs. GAI. Dependent variable is $\log(sales_{i,t})-\log(sales_{i,t-1})$.

Table 1.2 Simple slope analysis

	Effects of DAD	S. E.
High Competition	0.679	0.380*
Low Competition	-0.256	0.136*
High Quality	-0.589	0.259*
Low Quality	1.013	0.176**

*p< .05; **p< .001

From the simple slope analysis reported in Table 1.2, it can be seen that when competition intensity is high, the DAD attribute increases box office (β = .679, p < .05). However, when competition intensity is low, the DAD attribute decreases box office (β = -.256, p < .05). In addition, when movie quality is expected to be high, the DAD attribute decreases box office (β = -.589, p < .05), However, when movie quality is low, the DAD attribute increases box office (β = 1.013, p < .001).

1.5.5 Robustness Analysis

To enhance my confidence in the results above, I conducted several robust tests described below:

(1) I conducted analysis with equal weight of all attributes, and the results are consistent.

(2) I used another estimation method to eliminate some of the unobserved heterogeneity resulted from omitted variable bias. The fixed-effect model also controls for both movie-specific and period-specific fixed effects.

(3) *Competition* is measured as a variation of the Herfindahl-Hirschman Index but based on market share of box office rather than the number of screens.

(4) *Quality* is measured as the mean of critic reviews published before a movie's release.

Table 1.3 Robustness analysis

		Model 3 Attribute importance is equal weighted.		Model 4 Movie and week specific fixed-effect model		Model 5 Competition is measured as variation of HHI by box office.		Model 6 Quality is measured as critic ratings	
		Coef.	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**	**Coef.**	**S.E.**
Main Effects									
D_DAD		.047	.099	-.390	.502	.155	.297	.395	.338
D_Competition		-9.597	4.469*	-4.270	2.205*	-.245	.152	-3.691	4.699
D_Quality		.140	.062*	.081	.048*	.028	.151	-.003	.008
Moderating Effects									
D_DAD × Competition	H1 supported	21.384	1.536***	5.053	2.688*	3.176	1.514*	21.917	3.673***
D_DAD × Quality	H2b supported	-.212	.013***	-.231	.111*	-.335	.036***	-.037	.001***
Control Variables									
D_Overall Valence		.175	.013***	.248	.042***	.201	.020***	.217	.040***
D_ Overall Volume		.0003	.0003	.0002	.0001*	.0002	.0001*	.0002	.0002
D_ Overall Variance		.100	.069	.050	.070	.097	.071	.111	.077
D_Log (Screens)		.735	.049***	.695	.044***	.737	.036***	.726	.055***
D_Log (Week)		-.918	.107***	-.881	.036***	-.894	.110***	-.899	.105***
D_Log (Box Office)		.134	.006***	.186	.044***	.140	.002***	.141	.006***
Intercept				5.860	.892***				

*p< .05; **p< .01; ***p< .001

Note: Model 4 is fixed effect model.

Critic reviews were collected from the Metacritic website (Chen, Liu, and Zhang 2012). Metacritic summarizes reviews from major critics and media outlets, such as *The Washington Post* and *The New York Times,* and assigns each critic review a score ranging from 0 to 100.

The results of robustness tests in Table 1.3 indicate that my findings still hold in different tests, thus demonstrating that our findings are immune to different measures of key variables.

1.6 GENERAL DISCUSSION

Offering new features in new products is not always a good idea (Thompson, Hamilton, and Rust 2005), and competitors can catch up quickly once a new feature is proved to be welcomed by consumers. In this study, I investigated how firms should deploy their limited R & D resources when competing with other firms on existing attributes of a product. I propose that firms can employ either a DAD strategy or a GAI strategy to increase sales, depending on the marketing conditions. The results of two experiments and a secondary data analysis show that, compared with a corresponding GAI product, a DAD product increases sales when product quality is low or when competition intensity is high. However, it leads to lower sales if the marketing condition is the opposite. And my findings demonstrate the advantages/disadvantages (i.e., greater consumer awareness and higher perceived risk) that a firm or a brand can expect to have with an outstanding attribute in its products.

1.6.1 Theoretical Contributions

I believe this research makes some valuable contributions to the current literature. This study contributes to the new product development literature by identifying two strategies that firms may *intentionally* use to improve their products and provides evidence that each strategy is likely to be more effective under different marketing situations (e.g., when competition intensity is high) in terms of increasing sales. As mentioned above, the previous literature focused on examining the effect of adding new features that other products do not have on product evaluations (Bertini, Ofek, and Ariely 2009; Gourville and Soman 2005; Okada 2006; Zhou and Nakamoto 2007) and largely ignored how firms should compete on common attributes. This study fills this gap. Second, one of the core issues in product design is to determine the values of product attributes. Product design literature, particularly that about conjoint analysis, is essentially about how consumers weigh and value different attributes and how firms should determine the performance levels of different attributes on the basis of similarity data or preference data elicited from consumers (e.g., Green and Srinivasan 1978). However, two limitation of conjoint analysis are that (1) it assumes that preferences are stable over time, which had been questioned by numerous research in consumer behavior and (2) it usually focuses on attributes, price, and brands (Green and Krieger 1991). So market conditions are usually not reflected in a conjoint analysis. Therefore, firms may find that their new models have similar attributes to each other or to existing products and therefore have to compete with each other head to head on price. What I found in this study could be used as a complement to conjoint analyses in the sense that product attribute choices based on conjoint analysis should be considered together with the psychological implications of having a dominant attribute. Moreover, such an implication has to be understood in the context of product- and environment-related characteristics. In this sense, I echo prior studies (e.g., Bloch 1995; Koukova, Kannan, and Kirmani 2012) that concluded that product design choices cannot be fully comprehended without considering the specific characteristics of the nature of the product and the market condition where the product competes. As I have demonstrated, consumers' response to a DAD or a GAI product could differ based on product factors, such as expected product quality, as well as on external factors, such as competitive intensity.

In addition, this research also adds to the behavior decision making literature. Specifically, although it has been well documented that consumers may make choices on the basis of relational property of alternatives in the choice sets, thus demonstrating compromise effect or asymmetric dominance effect (Simonson 1989; Huber, Payne, and Puto 1982), little is known about the boundary conditions of these effects. This research suggests two possible moderators of the compromise effect, namely expected product quality and competition intensity. A conclusion of my findings is that the compromise effect may not always manifest itself. In fact, lack of the ability to generate consumer awareness is an important but often ignored disadvantage of being the compromise, and the presence of the compromise effect depends on the relative strength of all advantages and disadvantages associated with being the middle. Sinn, Milberg, Epstein, and Goodstein (2005) find that consumers prefer the extreme options (or the dominant attribute products in this study) than the compromise option when the former are made by more familiar brands. Their findings is highly consistent with my framework because more familiar brand names certainly decrease perceived risk associated with extreme options and thus increase their likelihood of being chosen. Future research may consider other possible mechanisms as well and develop a more comprehensive framework to summarize the boundary conditions of these important effects.

1.6.2 Implications for Practice

This study also has important managerial implications. First, this study can guide managers to allocate their valuable yet limited R & D resources more wisely under different marketing situations. Specifically, my findings suggest that managers should scrutinize the competition environment carefully and then decide whether they should implement a DAD strategy or a GAI strategy. Furthermore, as time goes by and the environment changes, they should consider adjusting their resource allocation strategies accordingly.

My findings could also be applied to the new market entry context. Zhang and Markman (1998) suggest that it is a better strategy for firms who intend to enter a new market to compete with incumbents on existing features rather than add new features that the incumbents' current marketing offerings do not have. A follow-up question would be how to compete on existing features. As discussed at the beginning of this chapter, firms have at least two strategies they can use, and the extant literate provides few insights about which one is more effective. Considering that nowadays firms need to compete with one another mostly on providing aggregate levels of benefits, instead of offering any specific functionality to consumers, my findings deliver a clear message to managers who plan to move into a new market. That is, they need to first research the market and find the most important (abstract) benefits that consumers look for. And then they should evaluate current marketing offerings and determine the average performance. Armed with this knowledge, they can find out which strategy they should use based on the relevant market condition.

Last but not the least, research regarding emerging markets shows that consumers at the bottom of the social class pyramid are unwilling to take risks (Nakata and Weidner 2012). As a result, despite the fact that the change in behavioral habits and the extension of their physical limitations brought about by new products could benefit them tremendously and substantively, they are generally reluctant to adopt new products. Given that this group of consumers usually does not purchase high-end products, my findings suggest that firms who target this group of consumers may examine the current products they are using and launch a new product that has significant enhancement on a particular attribute, with other attributes largely intact in comparison with the products that are already in use. Therefore, the findings of this study could provide guidance to a broad variety of practices, such as positioning, new market entry, and marketing communication.

1.6.3 Limitations and Future Research

In this study, I used both secondary data analysis and behavioral experiments to test our hypotheses. Although this mixed method gives me more confidence in my findings than if I had used only one, each method has its own limitations. For instance, brand names (Sony vs. Pandigital) may not be a perfect indicator of expected product quality, and the findings may be subject to some alternative explanations. And product evaluations may not reflect real purchases. It may be better to implement field (quasi-)experiments to test the hypotheses. In addition, in this study I examined the moderating roles of only two factors, namely, expected product quality and competition intensity. In future, the possible effects of more potential moderators should be investigated.

In addition, I proposed and tested two possible mechanisms by which a DAD design may influence sales and purchase intention. Other mediators, such as concerns about elaboration costs (Bettman, Luce, and Payne 1998), may exist and play a role. Future studies could shed light on this, allowing managers to better understand why a dominant attribute may lead to different marketing results. Finally, I used three product categories in this study: digital cameras, movies, and digital picture frames. All products are relatively cheap. Therefore, caution should be exercised when applying my findings to purchase contexts where the focal products are more expensive and consumers thus are more involved in their purchase decisions.

CHAPTER 2
USER REVIEWS VARIANCE, CRITIC REVIEWS VARIANCE, AND PRODUCT SALES: AN EXPLORATION OF CUSTOMER BREADTH AND DEPTH EFFECT

Online user reviews constitute a new element of the marketing communications mix that has the potential to significantly affect product sales. A general consensus holds that a positive valence of user reviews benefits product sales, yet the effect of variance is less intuitive and current findings are mixed. I argue that user reviews variance actually constitutes a double-edged sword that can either hurt or help product sales, depending on the variance of critic reviews and other quality signals. Three complementary studies in multiple industries (movies, digital cameras, and books) with multiple methods (secondary data analysis and behavioral experiment) reveal three key insights in this setting. First, after recognizing a high variance in user reviews, many potential buyers may simply exclude the focal product from their consideration sets for fear that the focal product may not be what they are looking for, which is termed the customer breadth effect. Second, high user reviews variance, in combination with high critic reviews variance, can elicit a sense of uniqueness and thus enhance purchase intentions of consumers, which is termed the customer depth effect. Third, quality signals (e.g., product cost and product extension) can strengthen the positive customer depth effect. The overall influence of user reviews variance on product sales thus depends on the relative strength of the customer breadth and depth effects. The eventual outcomes can be negative, insignificant, or even positive. These findings have critical theoretical and managerial implications.

2.1 INTRODUCTION

User reviews are product evaluations generated by regular users who provide product quality information largely based on their usage experience (e.g., whether and how a product matches their tastes and preferences) (Chen and Xie 2008; Khare, Labrecque, and Asare 2011). In practice, most firms and retailers adopt review systems that allow users to give overall ratings as well as narrative descriptions of their opinions (e.g., the pros and cons) about a product. The valence of reviews indicates the favorability of the product, which could be calculated as the mathematic mean of all overall ratings, and the variance of reviews reveals the inconsistency among reviews, which could be measured as the mathematic variance of these ratings (Moe and Trusov 2011; Sun 2012).

Due to the increasing popularity of social media (e.g., *Amazon*, *Facebook*, and *Yelp*), user reviews now constitute a new element of the marketing communications mix that has the potential to significantly affect purchasing (see Table 2.1 for a summary of representative studies). In general, most studies find that a positive valence of user reviews benefits product sales and a negative valence hurts sales. However, the effect of user reviews variance is less intuitive, and the existing empirical findings are mixed. For instance, Zhang (2006) shows that user reviews variance has no significant influence on box office sales, but Zhu and Zhang (2010) find that high variance exerts a negative effect on sales when the product is not popular. In contrast, Sun (2012) shows that high variance has a positive effect when the valence of user reviews is negative, and Moe and Trusov (2011) report similar findings. Therefore, further studies are needed to clarify the relationship between user reviews variance and sales. In theory, user reviews variance could have its own information value and thus affect various important financial outcomes such as willingness-to-pay and abnormal returns (Luo, Raithel, and Wiles 2013; Wu et al. 2013). In an extreme case, assume that half of prior buyers rate a product 5 out of 5, and the other half rate it 3 out of 5. Although the average rating is still 4, purchase decisions of potential consumers in this case could be very different from when all prior buyers give the focal product a rating of 4 out of 5.

In this study, I attempt to further explore the relationship between user reviews variance and sales. The core finding is that user reviews variance is a double-edged sword that can either hurt or help product sales, depending on the variance of critic reviews and other product signals. Critic reviews are product evaluations generated by third-party professional critics who have specialized knowledge about a product category (Basuroy, Desai, and Talukdar 2006; West and Broniarczyk 1998). Nowadays, critic reviews are also very common and can be easily accessed by potential buyers. Although numerous studies have investigated the effects of user reviews or critic reviews separately (see Table 2.1), to the best of my knowledge very few existing studies have examined their joint effect, although doing so is both practically and theoretically important. Practically, both user reviews and critic reviews are easily available online. Many popular online platforms such as *Consumer Reports*, *Rotten Tomatoes*, and *CNET* even present these two types of reviews side by side for consumers' convenient use. Given user reviews and critic reviews are materially different (see Table 2.2 for a summary of these differences), potential buyers likely consider both (Holbrook and Addis 2007; Moon, Bergey, and Iacobucci 2010). Ignoring either could dramatically impair managers' likelihood of managing online word-of-mouth activities appropriately and effectively. As my research demonstrates, ignoring critic reviews could lead to severe biases when estimating the effects of user reviews on sales.

Table 2.1 Prior research on the effects of user reviews (URs) and critic reviews (CRs)

Studies	Key URs metrics	Effects of URs	Key CRs metrics	Effects of CRs	How URs and CRs Work Jointly	Research context	Test mechanism
Eliashberg and Shugan 1997; Basuroy et al. 2003	×	×	Valence	Valence determines sales.	×	Movies	×
Chen, Liu, and Zhang 2012	×	×	Valence	Valence affects firm value.	×	Movies	×
Tellis and Johnson 2007	×	×	Valence	Valence affects firm value.	×	Electronics	×
Basuroy, Desai, and Talukdar 2006	×	×	Variance	Variance increases the effects of sequels and ads.	×	Movies	×
Duan, Gu, and Whinston 2008	Volume	Volume increases sales.	×	×	×	Movies	×
Godes and Mayzlin 2004	Volume	Volume increases sales.	×	×	×	TV show	×
Chintagunta, Gopinath, and Venkataraman 2010	Valence	Valence increases sales.	×	×	×	Movies	×
Chen, Wang, and Xie 2011	Valence	Valence increases sales.	×	×	×	Cameras	
Chevalier and Mayzlin 2006	Valence	Valence increases sales.	×	×	×	Books	×
Zhang 2006	Variance	Variance has no effect on sales.	×	×	×	Movies	×
Clemons, Gao, and Hitt 2006	Variance	Variance increases sales.	×	×	×	Beer	×
Moe and Trusov 2011	Variance	Variance increases sales.	×	×	×	Beauty products	×
Sun 2012	Variance	Variance helps sales for low-rated products.	×	×	×	Books	×
Zhu and Zhang 2010	Variance	Variance hurts sales for less popular products.	×	×	×	Games	×
Liu 2006	Volume	Volume increases sales.	Valence	Valence increases sales.	×	Movies	×
Moon, Bergey, and Iacobucci 2010	Valence	Valence increases sales. Ads enhance its effectiveness.	Valence	Ads enhance the effects of valence.	×	Movies	×
Holbrook and Addis 2007	Valence	Valence affects popular appeal.	Valence	Valence affects popular appeal.	URs valence mediates the effect of CRs valence.	Movies	×
Zhou and Duan 2012	Volume	Volume increases downloads.	Valence	Valence increases downloads.	URs volume mediates the effect of CRs valence.	Software	×
Our study	**Variance**	**Variance decreases sales.**	**Variance**	**CRs variance has no direct effect on sales.**	**The interactive effect is positive. Product quality enhances it.**	**Movies Cameras Books**	**Customer breadth and depth**

From a theoretical perspective, understanding the joint effect of user reviews and critic reviews is also important. On one hand, because both of them could mitigate information asymmetry between buyers and sellers, their effects could be redundant. Consequently, the presence of one type of reviews may mitigate the effect of the other. On the other hand, because user reviews and critic reviews tend to focus on different aspects of the same product (Moon, Bergey, and Iacobucci 2010; Holbrook 1999), their effects could be complementary. Exploring the joint effect of user reviews variance and critic reviews variance could shed some light on this important theoretical question whether user reviews and critic reviews are substitutive or complementary. In addition, considering the joint effect of user reviews variance and critic reviews variance also helps reconcile the inconsistent findings in prior literature and brings new insights on the boundary conditions of how user reviews variance affects sales. Last but not least, from an information integration perspective (Anderson 1968), it is intriguing to examine how consumers interpret information from different sources with probably unequal credibility (i.e., critic reviews are generally believed to be more credible than user reviews) and then arrive at a conclusion.

I conduct three complementary studies in multiple industries (movies, digital cameras, and books) with multiple methods (secondary data analysis and behavioral experiment). The results are highly consistent and provide support to my hypotheses. I make three theoretical contributions on the top of prior research:

First, few prior studies explain the mechanism of why user reviews variance impacts sales (see Table 2.1). Fang, Palmatier, and Grewal (2011) suggest that a firm can increase sales through both the breadth and depth of its customer assets. Specifically, a product could generate higher sales either by appealing to a mass customer base (i.e., customer breadth) or by ensuring that consumers in a niche market develop strong preferences (i.e., customer depth). Thus, a product that lacks customer breadth could still achieve high sales by enhancing customer depth. Using this framework, I find that user reviews variance has a Janus-like effect on sales. On one hand, it may impair sales by indicating mismatch risk, thus inducing a negative customer breadth effect. On the other hand, it may boost sales by increasing perceived uniqueness, thus eliciting a positive customer depth effect. These findings can certainly help managers to develop appropriate strategies to manage online word-of-mouth activities.

Second, to the best of my knowledge, this study is the first to test the joint effects of user reviews and critic reviews. Although critic reviews are relatively more consistent than user reviews, variance generally occurs among critic reviews too. For example, *Focus*, a smartphone manufactured by Samsung, received a score of 64 out of 100 from *Consumer Reports*, whereas *CNET* gave it a more favorable rating of 4 out of 5 stars. Studying the interactive effect of user reviews variance and critic reviews variance sheds light on how information from different sources (e.g., user reviews and critic reviews) together affect sales. My study finds that, quite surprisingly, high user reviews variance and high critic reviews variance together could actually increase sales. It also shows that focusing on user reviews variance while ignoring critic reviews variance could lead to severe biases in estimating the total effect of user reviews variance.

Third, although existing findings about the impact of the valence of user reviews are largely consistent, the results regarding the effect of user reviews variance are very mixed and need further examination. I find important boundary conditions that can reconcile the inconsistency of previous findings. Specifically, I show that critic reviews variance and other product quality signals (i.e., product cost and product type) can moderate and even reverse the supposedly negative impact of user reviews variance. Depending on critic reviews variance and other product quality signals, the overall effects of user reviews variance could be negative, insignificant, or even positive.

This study also has methodological advantages. Unlike most prior studies (see Table 2.1), I test my theories on both search and experience products and employ both secondary data analyses and an experiment to pin down the mechanism. The multi-context and multi-method research design used in this study enhances its internal and external validity.

In the following sections, I first build a conceptual framework and develop several specific hypotheses. I then report the results of three studies. Finally, I discuss the theoretical and managerial implications of this study, followed by discussions of limitations and future research directions.

Table 2.2 Online product reviews: user reviews and critic reviews

	User Reviews	Critic Reviews
Definitions	User reviews are generated by users on the basis of their personal usage experience and preferences (Chen and Xie 2008; Moon, Bergey, and Iacobucci 2010)	Critic reviews are generated by critics on the basis of independent lab testing and professional evaluation (Chen and Xie 2005; West and Broniarczyk 1998)
Characteristics	1) Users' usage experience, taste, preference (Chen and Xie 2008; Khare, Labrecque, and Asare 201; Sun 2012) 2) Attributes information (e.g., user-friendly, tastes good) (Chen and Xie 2008) 3) Represent "mass" tastes (Holbrook 1999; Holbrook and Addis 2007; Pan and Zhang 2011) 4) Consumers can find out group members' attitude and prior users' satisfaction, recommendation, and mismatch of preference (Chevalier and Mayzlin 2006; Liu 2006; Senecal and Nantel 2004; Sun 2012)	1) Lab tests, professional and expert evaluations (Chakravarty, Liu, and Mazumdar 2010; Chen and Xie 2005) 2) Technical performance information (e.g., technical and artistic specifications) (Chakravarty, Liu, and Mazumdar 2010; Chen and Xie 2008) 3) Represent "elite" tastes (Holbrook and Addis 2007; West and Broniarczyk 1998) 4) Consumers can find out functional performance, product attributes' index, and technological parameters (Basuroy, Desai, and Talukdar 2006; Chen, Liu, and Zhang 2012; West and Broniarczyk 1998)
Examples	1) Product reviews and ratings at *Amazon* 2) Movies, autos, and stocks reviews at *Yahoo!* 3) Restaurant recommendations at *Yelp* *4)* Conversations on games at *GameSpot* 5) Posts at *Facebook* and *Twitter*	1) Cellphone and laptop testing report at *ConsumerReports* 2) Stock recommendations at *The Wall Street Journal* 3) Critics' book reviews at *The New York Times Review of Books* 4) Movie and TV show columns at *Entertainment Weekly* 5) Editors' critic on tablets and cell phones at *CNET*

2.2 LITERATURE REVIEW AND HYPOTHESES

I build my conceptual framework in several steps. To begin with, I explore how high user reviews variance hurts product sales by reducing customer breadth and then investigate how user reviews variance in combination with critic reviews variance may help product sales by enhancing customer depth. Finally, I consider the effects of other product quality signals.

2.2.1 Customer Breadth Effect

Although some products such as Apple's iPad Mini earn overwhelming praise from consumers, many products are quite controversial. In the latter case, consumers usually experience various levels of benefits from the same product, and their reviews accordingly reflect their different usage experiences. More divergent reviews certainly lead to higher variance of user reviews. In extreme situations, the overall ratings contained in user reviews could distribute in a bipolar format, suggesting that consumers either love the product or hate it. Bipolar distribution may also arise because only extremely satisfied and extremely dissatisfied customers are involved in spreading word-of-mouth (Anderson 1998). Regardless of its origin (e.g., from a bipolar distribution or an even distribution), a large variance usually suggests that some like the product but others do not (Sun 2012; Luo, Raithel, and Wiles 2013).

Studies have found that user reviews variance has the potential to influence sales (Clemons, Gao, and Hitt 2006; Moe and Trusov 2011), although product or market characteristics may moderate its effect (Zhu and Zhang 2010). I propose that user reviews variance can elicit a customer breadth effect. That is, as user reviews variance increases, product sales may suffer because many customers will exclude the focal product from their consideration after they see the large variance.

In reality, the user reviews variance information could be quite conspicuous because of the way that retailers present it (e.g., *Amazon* shows variances in bar charts), so potential buyers can realize immediately whether all prior buyers like a product, even without reading the narrative messages contained in user reviews. Sun (2012) proposes that high user reviews variance indicates higher mismatch risk such that the focal product has a larger likelihood of not fitting a consumer's need. In other words, the lack of consensus among prior users makes potential buyers feel uncertain about whether they will like the product and they respond negatively to such uncertainty (Hogarth 1977; Jaccard and Wood 1988). Hence, given that other alternatives with lower user reviews variance are usually available on the market, a high variance could induce many prospective buyers not to consider the focal product any further, consequently decreasing its sales. I hypothesize the following:

H1: High user reviews variance decreases product sales, all else being equal.

The information provided by critic reviews variance is more complicated. Intuitively, critic reviews variance should have a similar or stronger customer breadth effect due to higher source credibility (Sternthal, Dholakia, and Leavitt 1978). However, as Table 2.2 shows, user reviews and critic reviews differ considerably. To potential buyers, high user reviews variance is unsurprising because users have diverse needs and tastes, and therefore their evaluations may differ. But high critic reviews variance could be unexpected because critics are supposed to evaluate the focal product objectively, and therefore more consistently (Holbrook 1999). Interpretation of the high critic reviews variance determines whether the customer breadth effect emerges. In case consumers believe that high critic reviews variance indicates that these critics are not qualified and thus discount the information value of their reviews, critic reviews variance should have little direct effects on sales (West and Broniarczyk 1998; Meyer 1981). Therefore, critic reviews variance may not necessarily elicit a negative customer breadth effect.

2.2.2 Customer Depth Effect

Consumers purchase products not only for what they do but also for what they mean (Berger and Heath 2007). Thus, if a consumer perceives a product as capable of signaling his or her unique self, his or her purchase intention may increase, especially for those with a high need for uniqueness (Bloch 1995; Simonson and Nowlis 2000). I propose that high user reviews variance, together with high critic reviews variance, could increase the perceived uniqueness of a focal product, consequently generating higher sales. The logic can be seen below.

Consumers are regarded to be cognitive misers (Tversky and Kahneman 1974) because they normally do not want to spend their limited cognitive resources on systematically processing information. Instead, according to the Elaboration Likelihood Model (ELM), they count on heuristics and salient but possibly non-diagnostic cues to make judgments unless they are alerted to involve more in information processing (Petty and Cacioppo 1986).

Unlike user reviews, critic reviews are written by experts who base their reviews on independent lab testing or professional evaluations. Therefore, critic reviews should be objective and consequently consistent[1] (Chen and Xie 2008; Holbrook 1999). If potential buyers

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[1] A survey administered to a national panel of 61 people supported this assumption. In this survey, participants were asked to respond to two questions about either user reviews or critic reviews: "How objective do you expect user reviews (critic reviews) to be?" and "How consistent do you expect user reviews (critic reviews) to be with each other?" on two 7-point scales (1=*not at all*, 7=*very much*). The results showed that participants did perceive critic reviews to be significantly more objective and consistent than user reviews.

unexpectedly find critic reviews have a high variance, they may be alerted and thus more systematically consider the review content. In a recent paper, Karmarkar and Tormala (2010) show that if an expert who is supposed to be confident in his judgment admits he is not, readers of his reviews will feel greater expectation violation than if the expert says the opposite. As a result, readers are involved more in the processing of available information and are persuaded more when the persuasive message is strong than when it is weak. Similarly, Ziegler, Diehl, and Ruther (2002) demonstrate that given that recipients expect experts to be likable and non-experts to be unlikable, they experience greater expectation violations if they realize the opposite is true. Consequently, recipients scrutinize messages more careful than if the expectation is met.

Based on these findings, I speculate that when prospective buyers find that critic reviews variance is high, they would be more willing to scrutinize and elaborate on information to make more accurate judgments. Accordingly, they may not prematurely exclude a product from consideration simply based on its high user reviews variance. Rather, they probably would read the narrative messages contained in user reviews, digest these comments, and try to understand which benefits they can get from the product before they make decisions. In this process, they are likely to realize that a product with a high user reviews variance is a niche product, and some of them may even find this product fit their preferences well (Sun 2012; Luo, Raithel, and Wiles 2013).

Unlike a mass-market product, a niche product caters to the needs of only a specific group of consumers, so it usually has both very strong and very weak attributes (Kim and Mauborgne 2005). This could make the product look special and unique to consumers, especially to target consumers, because selecting a niche product could be viewed as a declaration of preference for one attribute over another. Supporting this argument, Maimaran and Simonson (2011) find that consumers who look for unconventionality are more interested in mixed-value options with both advantages and disadvantages than all-average options. For instance, a hotel of high quality but also long distance from a city center is regarded as less conventional than a hotel of average quality and average distance from the center. So people who want their consumptions to express their unique selves are more likely to choose the mixed-value options. Simonson and Nowlis (2000) report similar findings.

In addition, because fewer consumers purchase niche products than mass-market products, a buyer of niche products does not need to worry about being overwhelmingly similar to others for consuming the same product they do. This could also generate a feeling of uniqueness (Berger and Heath 2007).

To sum up, I propose that high user reviews variance and high critic reviews variance together could elicit a feeling of uniqueness that may increase sales. I term this effect the customer depth effect. I hypothesize the following:

H2: High user reviews variance interacts with high critic reviews variance to increase product sales, all else being equal.

2.2.3 Moderating Effects of Product Cost and Product Type

Manufacturers also send out product quality signals to influence consumers' purchase decisions (Kirmani and Rao 2000). Potential buyers, therefore, are likely to consider review information along with other available signals. Although empirical work about the nature of interactions among multiple indicators of product quality is still rare (Kirmani and Rao 2000), it can be reasonably assumed that multiple signals may strengthen or weaken the influence of each other, depending on their congruity (Basuroy, Desai, and Talukdar 2006). Therefore, the negative customer breadth effect is likely to be mitigated when other signals suggest the focal product is of high quality. After all, if quality signals such as brand names suggest that the focal product is popular on the market, consumers' concern about the mismatch risk elicited by the high user reviews variance could be at least partially eliminated.

In addition, I speculate that product quality could amplify the positive customer depth effect. Prospective buyers who realize the focal product is unique would be more likely to purchase it if the product is of high quality than otherwise. As existing research notes (Simonson and Nowlis 2000; Tellis, Yin, and Niraj 2009), both uniqueness and quality are important values consumers look for when they purchase a product. Products that can satisfy both requirements are usually rarer than options that can meet either standard. In fact, zero-term heuristic suggests that consumers believe that all options are balanced, so for each option, the advantages of one attribute must be compensated for by the disadvantages of another (Chernev 2007). Thus, when information from different sources suggests that a product is not only of great quality but also of high uniqueness, consumers may find the focal product especially attractive and their product evaluations and purchase intention will increase even further. Therefore, the customer depth effect will be amplified.

I consider two product quality signals in the current research: product cost and product type (Basuroy, Chatterjee, and Ravid 2003; Basuroy, Desai, and Talukdar 2006). Higher product cost generally translates into sophisticated designs, advanced technologies, and reliable functions, so high product cost could signal high product quality. For example, in the movie industry, Litman (1983) argues that big budgets promise higher quality. In my research, product type is defined as whether a product is the first model or an extension based on an earlier model in a product line. This concept is parallel to the construct of a sequel in the movie industry. For other products such as digital cameras, determining whether a specific model is the first model or an extension usually is easy. For instance, Nikon F was the first product in the 35mm SLR line with manual focus, and the next two generations, Nikon F2 and F3, were extensions of the same line. Product extensions are often built upon the success of the first model, so consumers may infer the quality of a product on the fact that it is an extension (Basuroy, Desai, and Talukdar 2006). For instance, movie sequels are typically found to generate higher box office revenues (Moon, Bergey, and Iacobucci 2010). I thus hypothesize the following:

H3: The positive interactive effect of high user and critic reviews variances on product sales is strengthened when the product cost is high rather than when it is low.

H4: The positive interactive effect of high user and critic reviews variances on product sales is strengthened when the product is an extension of a product line rather than when it is a new product.

2.3 STUDY 1

2.3.1 Research Context

I focus on the U.S. movie industry in the first study for two reasons. First, movies represent experience products characterized by information asymmetry between firms and buyers (Elberse and Eliashberg 2003). Moviegoers thus must rely extensively on external reviews (Liu 2006) and movie characteristics (Basuroy, Chatterjee, and Ravid 2003; Basuroy, Desai, and Talukdar 2006) as quality signals. Second, this important industry earns annual domestic revenues of more than $10 billion. My sample consists of 136 movies released between December 2009 and

December 2010. In Table 2.3, I describe the constructs, measures, and data sources for Study 1, as well as those in Study 2.

2.3.2 Measurement and Data Sources

Product sales. Consistent with Dellarocas, Zhang, and Awad (2007), I obtained weekly box office data from *Box Office Mojo*, a feature of the *Internet Movie Database* (*IMDb*). I collected weekly box office data for the first eight weeks after a movie opened; this period accounts for approximately 97% of the total box office (Liu 2006). If a movie's lifetime was shorter than eight weeks, I collected the weekly box office data in its entire life circle.

User and critic reviews variances. I collected user reviews from *Yahoo! Movies* (Chintagunta, Gopinath, and Venkataraman 2010; Moon, Bergey, and Iacobucci 2010) and critic reviews from *Metacritic* (Chen, Liu, and Zhang 2012). *Metacritic* summarizes reviews from major media outlets, such as *Variety*, *The Washington Post*, *Rolling Stone*, and *The New York Times*. The critics' ratings range from 0 to 100. Users' ratings on *Yahoo! Movies* range from F to A+. Therefore, I transformed the users' ratings to numeric values from 1 (F) to 13 (A+) (Moon, Bergey, and Iacobucci 2010).

I collected critic reviews posted before a movie's release (Chen, Liu, and Zhang 2012) because almost no critic reviews appeared thereafter. I also collected user reviews from the opening week to the eighth week (Liu 2006; Moon, Bergey, and Iacobucci 2010).

To measure variance, I used the standard deviation of users' or critics' ratings (Moe and Trusov 2011; Sun 2012). Specifically, because all prior reviews may affect the decisions of future moviegoers (Moon, Bergey, and Iacobucci 2010), user reviews variance is measured as the standard deviation of the cumulative user reviews from the opening week.

Table 2.3 Variables, measures, and data sources

Variables	Study 1: meanings and measures (data sources)	Study 2: meanings and measures (data sources)
Dependent variables		
Sales	Weekly box office (dollars; log-transformation; *Box Office Mojo*)	Sales rank in digital camera category (log-transformation; *Amazon*)
Independent variables		
User reviews variance	Standard deviation of cumulative user reviews from opening week (*Yahoo!*)	Standard deviation of cumulative user reviews (*Amazon*)
Moderators		
Critic reviews variance	Standard deviation of critic reviews published before a movie's release (*Metacritic*)	Standard deviation of critic reviews (*TestSeek*)
Product cost	Production budget (millions of dollars; log-transformation and mean-centered; *Box Office Mojo*)	Camera's list price, divided by the average price in its category (SLR or Compact), minus 1(dollars; *Amazon*)
Product extension	1 = sequel, 0 = new movie (*IMDb*)	1=improved model in a series; 0=new model in a series (*Digital Photography Review*)
Control variables		
User reviews volume	Cumulative number of user reviews from opening week (*Yahoo!*)	Cumulative number of user reviews from launch date (*Amazon*)
User reviews valence	Mean of user reviews from opening week (*Yahoo!*)	Mean of user reviews from launch date (*Amazon)*
Critic reviews volume	Total number of critic reviews published before movie's release (*Metacritic*)	Total number of critic reviews (*TestSeek*)
Critic reviews valence	Mean of critic reviews published before movie's release (*Metacritic*)	Mean of critic reviews (*TestSeek*)
Week	The number of weeks from initial release to the week of dependent variable (log-transformation; *Box Office Mojo*)	The number of weeks from launch date to data collection date (log-transformation; *Digital Photography Review*)
Screen	The number of screens at the week of dependent variable (log-transformation; *Box Office Mojo*)	
Competition	Market share of top 10 movies at the week of dependent variable (*Box Office Mojo*)	
Studio	1=distributed by major studio,0=others (*IMDb*)	
MPAA	MPAA ratings,1=R movies, 0=other (*IMDb*)	
Genre	Movie genre, 1=comedy, 0=other (*IMDb*)	
Weekend	1=opened on weekend, 0=other (*IMDb*)	
Season	1=opened on major holidays, 0=other (*IMDb*)	
Summer	1=opened in summer (May, June, and July), 0=other (*IMDb*)	
SLR		1=SLR model, 0= compact model (*Digital Photography Review*)
Canon		1= Canon, 0= other brands (*Digital Photography Review*)
Nikon		1= Nikon, 0= other brands (*Digital Photography Review*)
Sony		1= Sony, 0= other brands (*Digital Photography Review*)

Note: IMDb = Internet Movie Database.

Product cost and extension. I measured product cost as movie budget (Litman1983; Litman and Ahn 1998). To measure product type (extension or new product), I determined if a movie was a sequel (sequel = 1, new movie = 0) (Basuroy, Desai, and Talukdar 2006).

Control variables. I considered several control variables. First, I controlled for user reviews valence and volume, which also might influence box office revenues (Chevalier and Mayzlin 2006; Eliashberg and Shugan 1997). Valence represents the mean of all users' overall ratings from the opening week (Chintagunta, Gopinath, and Venkataraman 2010). Volume refers to the cumulative number of reviews from the opening week (Chintagunta, Gopinath, and Venkataraman 2010).

Second, to control for the potential interactive effects among variance, valence, and volume of user reviews, I added three interaction terms—user reviews variance × valence, user reviews variance × volume, and user reviews valence × volume (Chintagunta, Gopinath, and Venkataraman 2010). Moreover, because quality would influence the effect of user reviews variance on product sales (Sun 2012; Zhu and Zhang 2010), I controlled the interaction between product cost and user reviews variance.

Third, I controlled for movie-specific effects such as genre and Motion Picture Association of America (MPAA) ratings. I coded both as dummy variables: *genre* was equal to 1 if the movie was a comedy and 0 otherwise (Liu 2006); and *MPAA* took a value of 1 if the movie was rated R and 0 otherwise (Moon, Bergey, and Iacobucci 2010).

Fourth, I used a *week* variable to denote the number of weeks since the movie's release to the week in which I measured the dependent variable (Basuroy, Desai, and Talukdar 2006).

Fifth, the *screen* control variable measured the number of screens on which the movie was playing each week (Liu 2006; Elberse and Eliashberg 2003).

Sixth, to control for the effect of distributors, I used the dummy variable *studio*, which took a value of 1 if one of the eight major studios (MGM/UA, BV, Fox, Sony, Warner Bros, Miramax, Paramount, and Universal) distributed the movie and 0 otherwise (Basuroy, Desai, and Talukdar 2006).

Seventh, release dates influence box office revenues such that weekend and holiday releases attract more moviegoers (Radas and Shugan 1998). I therefore used three dummy variables: *weekend*, which took a value of 1 if a movie opened on a weekend (Friday, Saturday, or Sunday) and 0 otherwise (Duan, Gu, and Whinston 2008); *season*, which equaled 1 if the movie opened on one of seven major holidays (Thanksgiving, Christmas, New Year's, President's Day, Memorial Day, Independence Day, or Labor Day) and 0 otherwise (Moon, Bergey, and Iacobucci 2010); and *summer*, which took a value of 1 if the movie opened during the summer months (May, June, or July).

Eighth, market competition could also influence box office revenues (Litman and Ahn 1998), so I controlled for the total market share of the top 10 movies in any particular week.

Ninth, I included the box office revenue of the prior week to control for state dependence (Moon, Bergey, and Iacobucci 2010).

After matching the data from multiple sources, the final sample consists of 136 movies over an eight-week period. Table 2.4 summarizes the descriptive statistics of these key variables.

2.3.3 Model specification

To test my hypotheses, I needed to address some methodological concerns. First, I created a time lag between the independent variables and sales to eliminate the possibility of reverse causality (Boulding and Staelin 1995).

Second, because box office revenues were right-skewed, I used the log-transformation of weekly values (Elberse and Eliashberg 2003), after which the skewness and kurtosis values suggested a normal distribution.

Third, I assessed multivariate multicollinearity by examining the variance inflation factor (VIF). The VIF values ranged from 1.054 to 6.383, lower than the threshold of 10, so multicollinearity was not a serious issue (Kleinbaum, Kupper, Nizam, and Muller 2007).

Fourth, I recognized that critic reviews likely affected user reviews and thus led to endogeneity concerns (Holbrook and Addis 2007; Liu 2006; West and Broniarczyk 1998). I therefore followed the approach proposed by Luo, Rindfliesch, and Tse (2007) and regressed the variance, valence, and volume of critic reviews on user reviews variance, and then took the residual term as the new measure of user reviews variance. This residual term represented the component not explained by critic reviews information. I similarly created user reviews valence and volume measures.

Fifth, the three aspects of user reviews—variance, valence, and volume—may not be independent and exogenous (Liu 2006; Moe and Trusov 2011). For example, the volume and valence of prior user reviews might affect current variance (Moe and Trusov 2011). In my sample, previous user reviews valence significantly affected current variance and volume, and previous user reviews variance and volume significantly affected current valence. Therefore, I used a dynamic simultaneous equations model (Basuroy, Desai, and Talukdar 2006; Elberse and Eliashberg 2003) to account for the expected dynamic interrelationships among variance, valence, and volume of user reviews by treating them as endogenous variables. I also allowed

Table 2.4 Descriptive statistics and correlations

	Mean		Standard Deviation		Correlations								
	Study 1	Study 2	Study 1	Study 2	1	2	3	4	5	6	7	8	9
1.Sales [a]	10.96	2092.80	19.67	2052.01	1	.04	-.02	-.41	.07	-.12	-.20	.14	-.14
2. User Review Variance	3.69	1.17	.72	0.31	-.16	1	-.73	.02	.19	-.41	-.37	-.25	.01
3. User Review Valence	8.76	4.07	1.83	0.46	.20	-.72	1	.13	-.22	.51	.43	.35	.00
4. User Review Volume	403.42	109.47	492.08	126.08	.24	-.02	.02	1	-.16	.23	.43	-.06	.07
5. Critic review Variance	14.68	9.80	4.09	2.92	-.02	.08	-.08	.13	1	-.52	-.26	-.09	.10
6. Critic review Valence	58.15	76.28	13.60	7.15	.20	-.35	.38	.13	-.16	1	.57	.49	.11
7. Critic review Volume	12.76	26.79	13.96	17.16	.26	-.10	.17	.27	.04	.38	1	.17	.07
8. Product Cost	68.86	616.72	56.43	998.90	.36	-.16	.16	.43	.05	.19	.36	1	.04
9. Product Extension	0.15	0.31	0.36	0.46	.12	.04	.05	.05	-.05	-.02	-.06	.09	1

Notes: For Study 1, sales and product cost are in millions of dollars; for Study 2, sales are sales ranks, and product cost is in dollars.
The correlations for Study 1 (2) are reported below (above) the diagonal.
Study 1 (2) $r > .05$ (.09) and $r < -.05$ (-.09) are significant at $p < .05$.

errors in my equations system to correlate in each week in order to account for the possibility that variables that did not appear in the model could simultaneously influence box office and user reviews variance, volume, and valence. In the model in which I estimated user reviews, I did not include critic reviews variables because they did not affect the component residual.

Sixth, the number of weekly screens may not be exogenous (Basuroy, Desai, and Talukdar 2006). User reviews and critic reviews could influence exhibitors' or studios' decisions (i.e., the number of screens). To capture the dynamic interrelationships, I added an equation into the above simultaneous system with screens as a dependent variable. Following Elberse and Eliashberg (2003), I log-transformed the number of weekly screens. Thus, I list the system of five estimated equations below:

$$
\begin{aligned}
(1)\ \ \text{Log}(\text{Sales}_{i,t}) = {} & \alpha_{1,0} + \beta_{1,1}\text{URs VarianceR}_{i,t-1} + \beta_{1,2}\text{CRs Variance}_{i} + \beta_{1,3}\text{Product Cost}_{i} \\
& + \beta_{1,4}\text{Product Extension}_{i} + \beta_{1,5}\text{URs VarianceR}_{i,t-1} \times \text{CRs Variance}_{i} \\
& + \beta_{1,6}\text{URs VarianceR}_{i,t-1} \times \text{CRs Variance}_{i} \times \text{Product Cost}_{i} \\
& + \beta_{1,7}\text{URs VarianceR}_{i,t-1} \times \text{CRs Variance}_{i} \times \text{Product Extension}_{i} \\
& + \beta_{1,8}\text{URs VolumeR}_{i,t-1} + \beta_{1,9}\text{URs ValenceR}_{i,t-1} \\
& + \beta_{1,10}\text{CRsVolume}_{i} + \beta_{1,11}\text{CRs Valence}_{i} \\
& + \beta_{1,12}\text{URs ValenceR}_{i,t-1} \times \text{CRs Valence}_{i} \\
& + \beta_{1,13}\text{URs ValenceR}_{i,t-1} \times \text{URs VarianceR}_{i,t-1} \\
& + \beta_{1,14}\text{URs ValenceR}_{i,t-1} \times \text{URs VolumeR}_{i,t-1} \\
& + \beta_{1,15}\text{URs VolumeR}_{i,t-1} \times \text{URs VarianceR}_{i,t-1} \\
& + \beta_{1,16}\text{Product Cost}_{i} \times \text{URs VarianceR}_{i,t-1} \\
& + \beta_{1,17}\text{Competitiont}_{t} + \beta_{1,18}\log(\text{Week}_{i,t}) + \beta_{1,19}\log(\text{Screen}_{i,t}) + \beta_{1,20}\text{MPAA}_{i} \\
& + \beta_{1,21}\text{Studio}_{i} + \beta_{1,22}\text{Weekend}_{i} + \beta_{1,23}\text{Season}_{i} + \beta_{1,24}\text{Summer}_{i} + \beta_{1,25}\text{Genre}_{i} \\
& + \beta_{1,26}\log(\text{Sales}_{i,t-1}) + \varepsilon_{1,i,t}
\end{aligned}
$$

$$
\begin{aligned}
(2)\ \ \text{URs VarianceR}_{i,t} = {} & \alpha_{2,0} + \beta_{2,1}\text{URs VolumeR}_{i,t-1} + \beta_{2,2}\text{URs ValenceR}_{i,t-1} + \beta_{2,3}\text{Product Cost}_{i} \\
& + \beta_{2,4}\text{Product Extension}_{i} + \beta_{2,5}\log(\text{Week}_{i,t}) + \beta_{2,6}\text{MPAA}_{i} + \beta_{2,7}\text{Studio}_{i} \\
& + \beta_{2,8}\text{Weekend}_{i} + \beta_{2,9}\text{Season}_{i} + \beta_{1,10}\text{Summer}_{i} + \beta_{2,11}\text{Genre}_{i} + \beta_{2,12}\log(\text{Sales}_{i,t-1}) + \varepsilon_{2,i,t}
\end{aligned}
$$

$$
\begin{aligned}
(3)\ \ \text{URs VolumeR}_{i,t} = {} & \alpha_{3,0} + \beta_{3,1}\text{URs VarianceR}_{i,t-1} + \beta_{3,2}\text{URs ValenceR}_{i,t-1} + \beta_{3,3}\text{Product Cost}_{i} \\
& + \beta_{3,4}\text{Product Extension}_{i} + \beta_{3,5}\log(\text{Week}_{i,t}) + \beta_{3,6}\text{MPAA}_{i} + \beta_{3,7}\text{Studio}_{i} \\
& + \beta_{3,8}\text{Weekend}_{i} + \beta_{3,9}\text{Season}_{i} + \beta_{1,10}\text{Summer}_{i} + \beta_{3,11}\text{Genre}_{i} + \beta_{3,12}\log(\text{Sales}_{i,t-1}) + \varepsilon_{3,i,t}
\end{aligned}
$$

$$\text{(4) URs ValenceR}_{i,t} = \alpha_{4,0} + \beta_{4,4}\text{URs VarianceR}_{i,t-1} + \beta_{4,5}\text{URs VolumeR}_{i,t-1} + \beta_{4,3}\text{Product Cost}_i + \beta_{4,4}\text{Product Extension}_i + \beta_{4,5}\log(\text{Week}_{i,t}) + \beta_{4,6}\text{MPAA}_i + \beta_{4,7}\text{Studio}_i + \beta_{4,8}\text{Weekend}_i + \beta_{4,9}\text{Season}_i + \beta_{4,10}\text{Summer}_i + \beta_{4,11}\text{Genre}_i + \beta_{4,12}\log(\text{Sales}_{i,t-1}) + \varepsilon_{4,i,t}$$

$$\text{(5) Log(Screen}_{i,t}) = \alpha_{5,0} + \beta_{5,1}\text{URs VarianceR}_{i,t-1} + \beta_{5,2}\text{URs VolumeR}_{i,t-1} + \beta_{5,3}\text{URs ValenceR}_{i,t-1} + \beta_{5,4}\text{CRs Variance}_i + \beta_{5,5}\text{CRsVolume}_i + \beta_{5,6}\text{CRs Valence}_i + \beta_{5,7}\text{Product Cost}_i + \beta_{5,8}\text{Product Extension}_i + \beta_{5,9}\log(\text{Week}_{i,t}) + \beta_{5,10}\text{MPAA}_i + \beta_{5,12}\text{Studio}_i + \beta_{5,13}\text{Weekend}_i + \beta_{5,14}\text{Season}_i + \beta_{5,15}\text{Summer}_i + \beta_{5,16}\text{Genre}_i + \beta_{5,17}\log(\text{Sales}_{i,t-1}) + \varepsilon_{5,i,t}$$

where CRs = critic reviews, URs = user reviews, and URs VarianceR (VolumeR, ValenceR) = residual of user reviews variance (volume, valence) not explained by critic reviews information.

2.3.4 Estimation results

I first included all independent and control variables, and then added the three interaction terms. I report the results in Table 2.5. To examine interactive effects further, I conducted simple slope analyses such that I avoided the need to create subgroups from continuous independent variables (Aiken and West 1991). Specifically, I split the moderators into high (two standard deviations above the mean) and low (two standard deviations below the mean) groups and estimated whether the effect of user reviews variance on box office revenues differs in different cases, as I outlined in Table 2.6.

Regarding the effects of the control variables, the results are consistent with those in prior studies. For instance, user reviews valence is found to increase box office revenues (Moon, Bergey, and Iacobucci 2010). Higher critic reviews valence and more screens increase revenues as well (Basuroy, Chatterjee, and Ravid 2003; Elberse and Eliashberg 2003). Moreover, the interaction between user reviews volume and valence increases box office, and the interaction between user reviews valence and variance decreases box office (Chintagunta, Gopinath, and

Venkataraman 2010). Furthermore, box office decreases over time (Basuroy, Desai, and Talukdar 2006); a higher box office in the prior week positively affects the current week's box office (Moon, Bergey, and Iacobucci 2010). Comedies and movies released by major studios also earn higher box office revenues (Moon, Bergey, and Iacobucci 2010). These results further provide face validity for my estimation results.

More importantly, the results in Table 2.5 indicate a negative effect of user reviews variance on sales (β = -.155, p < .01) in support of H1. The interaction between user and critic reviews variances is also significant (β = .006, p < .05), which supports H2. H3 and H4 are also supported because both movie budget (β = .003, p < .05) and sequel (β = .0088, p < .01) positively moderate the interactive effect between user and critic reviews variances.

The simple slope analysis (see Table 2.6) suggests that when the movie budget is high, user reviews variance has a significantly positive effect on movie box office if critic reviews variance is also high (β = .090, p < .05), but this effect becomes negative if critic review variance is low (β = -.085, p < .05). If the movie budget is low, however, user reviews variance has a significantly negative effect, regardless of the level of critic reviews variance (β = -.110, p < .05 when critic reviews variance is high; β = -.142, p < .001 when critic reviews variance is low). For sequels, user reviews variance has a significantly positive effect on box office revenues if critic reviews variance is also high (β = .193, p < .01), and the effect becomes negative when critic reviews variance is low (β = -.056, p < .05). For new movies, user reviews variance has a significantly negative effect when critic reviews variance is low (β = -.113, p < .001). This effect is no longer significant when critic reviews variance is high (β = -.008, n.s.).

Table 2.5 Effects of user reviews variance and critic reviews variance on movie box

	Hypotheses	Dependent variable = log(Weekly box office)					
		Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Main effects							
URs variance	H1 Supported	-.0578	.0270*	-.1319	.0562**	-.1549	.0563**
CRs variance		-.0003	.0027	-.0005	.0027	-.0018	.0028
Product cost		.0808	.0156***	.0736	.016***	.0779	.0167***
Product extension		-.0334	.0287	-.0308	.0287	-.0213	.0289
Moderating effects							
URs variance × CRs variance	H2 Supported			.0052	.0030*	.0064	.0035*
URs variance × CRs variance × Product cost	H3 Supported					.0026	.0013*
URs variance × CRs variance × Product extension	H4 Supported					.0088	.0034**
Control variables							
URs volume		.00003	.00003	.00004	.00003	.00004	.00003
URs valence		.0495	.0301*	.0531	.0317 *	.0549	.0315*
CRs volume		.0002	.0025	.0001	.0025	.0005	.0024
CRs valence		.0079	.0009***	.0076	.0009***	.0078	.0009***
UR valence × CRs valence		.0011	.0005*	.0010	.0006*	.0011	.0006*
URs variance × URs valence		-.0269	.0093**	-.0292	.0094**	-.0280	.0096**
URs volume × URs valence		.00004	.00002*	.00004	.00002*	.00004	.00002*
URs variance × URs volume		.0002	.0001*	.0002	.0001*	.0002	.0001*
URs variance × Product cost		.0294	.0189	.0393	.0234	-.0456	.0499
Competition		.2487	.2351	.2523	.2348	.3115	.2354
Log (Weeks)		-.2292	.0493***	-.2237	.0494***	-.2440	.0494***
Log (Screens)		.2113	.0248***	.2135	.0247***	.2342	.0250***
MPAA		-.0607	.0248**	-.0624	.0247**	-.0575	.0247**
Studio		.0371	.0236	.0407	.0236*	.0439	.0236*
Weekend		-.0170	.0339	-.0202	.0339	-.0199	.0340
Season		.0551	.0660	.0653	.0662	.0783	.0670
Summer		.0236	.0574	.0274	.0881	.0287	.0795
Genre		.1062	.0258***	.1019	.0249***	.0989	.0257***
Log (lagged box office)		.8160	.0221***	.8162	.0221***	.7974	.0224***
Intercept		.3760	.3301	.3617	.3298	.4837	.3300
N		826		826		826	
R^2		.971		.972		.973	
Incremental R^2 change (F-test)				.001*		.001***	

**p*< .05; ***p*< .01; ****p*< .001 (One-tailed).

Table 2.6 Simple slope analysis: Effects of user reviews variance on sales

	Effects of user reviews variance on sales	
	High critic reviews variance	Low critic reviews variance
High product cost	.090 (.056) *	-.085 (.041) *
Low product cost	-.110 (.054) *	-.142 (.040) ***
Sequels	.193 (.081) **	-.056 (.031) *
New movies	-.008 (.043)	-.113 (.038) ***

**p*< .05; ***p*< .01; ****p*< .001 (One-tailed). Notes: Standard errors are in parentheses.

2.3.5 Ad-hoc analysis: Ignoring interactive effects leads to biases

I also calculated the marginal effect of user reviews variance (i.e., the units of sales change contributed by one unit of user reviews variance increase) with and without considering critic reviews variance. This way, I can identify the level of "biases" resulting from the failure to consider the joint effect. Following Sridhar and Srinivasan (2012), I obtained the marginal effect from equation (1) in the simultaneous equations model above. Taking the two-way interaction as an example, I rearranged the terms in equation (1):

(6) $$Sales = exp^{[\beta_1 URs\,Variance\,+\,\beta_2 CRs\,Variance\,+\,\beta_5 URs\,Variance\,\times\,CRs\,Variance\,+other\,terms]}$$
$$= exp^{[(\beta_1 +\,\beta_5 CRs\,Variance)\times URs\,Variance\,+\,\beta_2 CRs\,Variance\,+other\,terms]}$$

So the marginal effect of user reviews variance is:

(7) $$\frac{\text{D (Sales)}}{\text{d (URs Variance)}} = (\beta_1 +\ \beta_5 CRs\,Variance) \times exp^{[(\beta_1 +\,\beta_5 CRs\,Variance)\times URs\,Variance\,+\,\beta_2 CRs\,Variance\,+other\,terms]}$$
$$= (\beta_1 +\ \beta_5 CRs\,Variance) \times Sales$$

To examine the bias in user reviews variance's marginal effect when critic reviews variance was omitted, I first estimated a model without critic reviews. Specifically, I included only user reviews variables and control variables and calculated the marginal effect of user reviews variance. Second, I calculated the marginal effect (equation (7)) when critic reviews interacted with user reviews. I assumed that the critic reviews variance and the box office revenue (sales) were equal to their sample means in Table 2.3 (Sridhar and Srinivasan 2012). The results show that without considering critic reviews variance, the marginal effect of user reviews variance is overestimated by 18.18%. Similarly, for three-way interactions, the results also suggest severe biases. For instance, for high-cost products, without considering critic reviews variance, the marginal effect is overestimated by 252.09%; for extension products, without considering critic reviews variance, the marginal effect is overestimated by 168.24%.

2.4 STUDY 2

2.4.1 Research context

In Study 2, I focus on the digital camera industry in an attempt to validate the findings in Study 1 to a different product category. Unlike movies, digital cameras represent a search product that consumers can try and evaluate prior to purchase (King and Balasubramanian 1994). The risk involved in purchasing digital cameras also is higher because of their high prices. In addition, prior studies used digital cameras as a focal product category to investigate the effect of online product reviews (Chen, Wang, and Xie 2011; Chen and Xie 2008; Li and Hitt 2010). Following methods of Chen, Wang, and Xie (2011), I collected data for 179 digital camera models on March 1, 2012, and May 1, 2012.

2.4.2 Measurement and Data Sources

Dependent variable: sales rank. Following prior studies (e.g., Chen, Wang, and Xie 2011; Chevalier and Mayzlin 2006; Sun 2012), I collected sales ranks of camera models at *Amazon* to measure product sales. Sales rank is the reverse of product sales, such that higher sales lead to lower ranks. Chevalier and Goolsbee (2003) confirm an approximately linear relationship between ln(sales) and ln(sales rank). Sales rank information for cameras is available in the "Camera, Photo & Video" category at *Amazon*, and I used the log-transformation of sales rank as the dependent variable.

User and critic reviews variances. On *Amazon*, users provide ratings ranging from 1 to 5 stars when they post reviews. I converted these star ratings into numerical values from 1 to 5 and collected all user reviews from the launch date to data collection date (Sun 2012). For the critic review, I relied on *TestSeek*, a critic review aggregator that is independent of manufacturers, retailers, and review publishers. It aggregates review data in real time from thousands of trusted publications. For digital cameras, it summarizes reviews from media outlets such as *CNET*, *Camera Labs*, *Stuff*, and *PhotographyBLOG*. These ratings range from 1 to 100, with 100 being the best score. I collected all critic reviews available on *TestSeek* for each camera model. Then I calculated critic and user reviews variance, volume, and valence, as in Study 1. Similar to Study 1, I regressed critic reviews information on user reviews variance, valence, and volume, and then took the residual terms as the new measures of user reviews variance, valence, and volume.

Product cost and extension. I measured product cost by the adjusted price of a particular camera model, which signals product quality (Rao 2005; Rao and Monroe 1989). Digital cameras can be classified as single-lens reflex (SLR) or compact, which have different cost structures. Therefore, I adjusted the prices by dividing them by the average price of all cameras in their own categories.

The price information came from *Amazon*. For the product extension dummy variable, 1 indicated a product extension and 0 referred to a new product. I coded a camera as an extension if it was the second or an updated model in a series.

Control variables. As in Study 1, I controlled for the effects of user reviews volume and valence, three interaction terms of user reviews, the interaction term between user reviews valence and critic reviews valence, and the interaction term between product cost and user reviews variance. Moreover, to control for the effect of the age of each camera model on sales (Chen, Wang, and Xie 2011), I determined each camera's launch date from *Digital Photography Review*. I used the variable *week* to measure the number of weeks since the initial launch date until data collection. I also used a dummy variable to control for SLR model. Finally, I used three dummy variables to differentiate three prominent brands in the digital camera industry, namely Canon, Nikon, and Sony, from other brands.

2.4.3 Estimation Results

As in Study 1, I constructed a simultaneous equations system to test my hypotheses. Table 2.7 presents the results. I find that user reviews variance has a positive effect on sales rank (β = 1.696, $p < .05$), indicating that higher user reviews variance decreases sales. Thus, H1 is supported since sales rank is negatively correlated with sales. The interaction between user and critic reviews variances has a negative effect on sales rank (β = -.131, $p < .05$), which supports H2. The product cost also negatively moderates the joint effect of user and critic reviews variances on the sales rank (β = -.207, $p < .01$), in support of H3. However, product type does not have a significant moderating effect (β = -.043, $p > .10$), so H4 is not supported.

Table 2.7 Effects of user reviews variance and critic reviews variance on camera sales rank

	Hypotheses	Dependent variable = log(sales rank)					
		Coef.	S. E.	Coef.	S. E.	Coef.	S. E.
Main effects							
URs variance	H1 Supported	.5220	.2681*	1.830	.810*	1.6963	.7078*
CRs variance		-.0293	.0270	-.0380	.0273	-.0416	.0272
Product cost		-.1183	.0858	-.1361	.0860	-.2100	.0921*
Product extension		.2135	.1351	.2558	.1369 *	.2365	.1354*
Moderating effects							
URs variance × CRs variance	H2 Supported			-.1297	.0782 *	-.1310	.0775*
URs variance × CRs variance × Product cost	H3 Supported					-.2071	.0997*
URs variance × CRs variance × Product extension	H4 not Supported					-.0430	.0458
Control variables							
URs volume		-.0017	.0010*	-.0017	.0011*	-.0017	.0010 *
URs valence		-3.7586	1.7997*	-3.8612	1.8643*	-3.3123	1.8616*
CRs volume		-.0116	.0059*	-.0113	.0059 *	-.0105	.0058 *
CRs valence		-.0174	.0160	-.0180	.0159	-.0123	.0160
URs valence × CRs valence		-.0532	.0250*	-.0415	.0258*	-.0445	.0257*
URs variance × URs valence		.0536	.5123	.0603	.5096	.1629	.5115
URs volume × URs valence		.0041	.0049	.0036	.0049	.0050	.0049
URs variance × URs volume		-.0117	.0055*	-.0118	.0055 *	-.0122	.0054 *
URs variance × Product cost		-.0901	.2920	-.0415	.2909	-.2025	.7189
Log (Weeks)		.6024	.2028**	.6434	.2037 **	.6151	.2017**
SLR		.2043	.2244	.1854	.2234	.0611	.2282
Canon		-.5082	.2282*	-.5575	.2286**	-.6115	.2272**
Nikon		.0765	.2148	.0605	.2136	.0321	.2119
Sony		.1794	.1951	.1841	.1940	.1862	.1921
Log (lagged sales rank)		.5238	.0577***	.5207	.0575***	.5172	.0567***
Intercept		2.7325	1.6229*	2.6869	1.6128*	2.4446	1.5963
N		179		179		179	
R^2		.696		.714		.735	
Incremental R^2 change (F-test)				.018*		.021*	

**p*< .05; ***p*< .01; ****p*< .001 (One-tailed).
Notes: sales rank is reversed coded. Lower sales rank indicates higher sales.

In addition, I also conducted the same simple slot analysis as I did in Study 1 whose results provided additional supports for my hypothesis. See Table 2.8 for regression parameters.

Table 2.8 Simple slope analysis: Effects of user reviews variance on sales

	Effects of user reviews variance on sales	
	High critic reviews variance	Low critic reviews variance
High product cost	-5.289 (2.715) *	.081 (.051) *
Low product cost	1.905 (1.153) *	1.902 (.703) ***
Improved cameras	-.863 (.765)	1.201 (.635) *
New cameras	-.203 (.663)	1.368 (.652) *

**p*< .05; ***p*< .01; ****p*< .001 (One-tailed). Notes: Standard errors are in parentheses.

2.5 STUDY 3

Study 3 is an experiment. The purpose of this study is to examine the mechanism through which user reviews variance influences sales. As I propose, high user reviews variance should lower customer breadth. However, it should increase customer depth by amplifying perceived uniqueness when critic reviews variance is also high.

2.5.1 Research Design

Subjects and design. A total of 242 subjects from a national panel participated in this study for monetary incentives. They were randomly assigned into one of four conditions of a 2 (user reviews variance: high vs. low) × 2 (critic reviews variance: high vs. low) between-subjects factorial design. Specifically, 59 participants were assigned to the low user variance and low critic variance condition, 63 participants were assigned to low user variance and high critic variance condition, and 60 participants were assigned to each of the other two conditions. Their average age is 33.4 years old, and 46.3% of them are male. Previous studies have used this panel to recruit study participants (Bagchi and Li 2011; Ward and Broniarczyk 2011).

Procedures and measures. This study was conducted on computers. At the beginning of the study, I informed participants that they needed to evaluate a book based on the review information provided. Specifically, I told participants to imagine that they were interested in a hard-copy novel entitled *The Call: A Novel,* written by Yannick Murphy. This book concerns a rural veterinarian and explores the catastrophes and joys that visit his family and patients, his workday observations, and his dark, soul-searching nights, all filtered through his medical log. The next screen presented user reviews information to participants. In one condition, the user reviews had an average rating of 4 out of 5 stars and the variance of the reviews was low (i.e., all ratings were 4 out of 5). In the other condition, the user reviews had the same average rating (i.e., 4 out of 5), but the variance of the reviews was high (i.e., some ratings were 5 out of 5, some were 4 out of 5, some 3 out of 5, etc.). Additionally, I also presented four example reviews with overall ratings and corresponding text messages (in which prior users described the pros and cons of the book). I presented the variance information in the same way as *Amazon* typically does for its products (see Figure 2 in Appendix). Specifically, the overall ratings and variances of reviews were presented in a bar chart. Participants could spend as much time as they wanted to read the review information before they moved on. On the next screen, participants reported their evaluations of the book on three 7-point scales (1=*not at all*, 7=*very much*) (i.e., "How desirable do you think this book is?" "How much do you like this book?" "How much are you interested in this book?"). These evaluations were referred to as the first-time evaluations. Participants then proceeded to the next screen and were told in the instructions that they also found relevant critic reviews information online and may also want to take it into consideration. Half of participants were told that all expert reviewers gave the focal book ratings of 4 out of 5, but the other half were informed that expert reviewers gave the book very different ratings (e.g., 5 out of 5, 4 out of 5, 3 out of 5, etc., although the average rating in both cases was 4 out of 5 stars). On the next page, the user reviews information was presented again in case participants wanted to re-read it. Participants were then asked to evaluate the book again using the same three-item scale. These evaluations were referred as the second-time evaluations. On the next screen they responded to two questions asking their perceived uniqueness of the book ("How unusual do you think this book is?" and "How unique do you think this book is?") on 7-point scales from 1 (not at all) to 7 (very much). Then participants reported how consistent user reviews and critic reviews were on scales from 1 (not consistent at all) to 7 (very consistent) and how familiar they were with the product category from 1 (not familiar at all) to 7 (very familiar). Finally, participants reported their demographic variables such as age and gender.

2.5.2 Results

Manipulation check. Participants in the low user reviews variance condition rated user reviews to be more consistent (M = 5.92) than those in the high user reviews variance condition (M = 3.43),

t (240) = 14.10, $p < .001$). Similarly, participants in the low critic reviews variance condition rated critic reviews to be more consistent ($M = 5.98$) than those in the high critic reviews variance condition ($M = 4.50$), t (240) = 7.19, $p < .001$). These results suggest that my manipulations of user reviews variance and critic reviews variance were successful.

Customer breadth effect. In my analyses below, I included familiarity with the product category as a covariate. Excluding this covariate from the analyses did not change my major findings. The product evaluation questions have nice reliability (*Cronbach's* $\alpha = .93$ for the first-time evaluation and *Cronbach's* $\alpha = .94$ for the second-time evaluation, respectively). An ANCOVA analysis with the first-time evaluations as the dependent variable, user variance as the independent variables, and familiarity as a covariant showed that user reviews variance had a significant effect on the first-time product evaluations. Specifically, product evaluation was higher when the user reviews variance was low than when it was high ($M = 4.36$ vs. $M = 3.52$), F (1, 239) = 19.81, $p < .001$), supporting the customer breadth effect. Familiarity also had a significant effect, F (1, 239) = 12.67, $p < .001$.

Customer depth effect: the interactive effect of user reviews variance and critic reviews variance. Because I was interested in testing the change of product evaluations elicited by the additional information about critic reviews variance, I created a new variable termed *evaluation change* by subtracting the first-time evaluations from the second-time evaluations. A positive value of evaluation change indicates that the second-time evaluation is higher than the corresponding first-time evaluation. I analyzed evaluation change as a function of user reviews variance, critic reviews variance, and their interaction in an ANCOVA analysis, using familiarity as a covariate. The results showed a significant two-way interaction (F (1, 237) = 5.98, $p < .02$). No other effects were significant, all ps > .30. Planned contrast showed that when user reviews variance was low, the variance of critic reviews did not have much effect on evaluation change ($M_{\text{user-low-critic-low}}$ = .54 vs. $M_{\text{user-low-critic-high}}$ =.08; F (1, 238) = 2.16, $p > .10$). However, when user reviews variance was high, evaluation change was significantly higher when the variance of expert reviews was high than when it was low ($M_{\text{user-high-critic-high}}$ = .85 vs. $M_{\text{user-high-critic-low}}$= .22; F (1, 238) = 3.97, $p < .05$), suggesting that high critic reviews variance increased product evaluations when the user reviews variance was high. Therefore, the customer depth effect was supported.

Mediated moderation. I tested the mediation role of perceived uniqueness in explaining the interactive effective of user reviews variance and critic reviews variance on evaluation change. Per Hayes (2013), two regression models were used to assess the indirect effects. The mediator model is: $M_e = \alpha_0 + \alpha_1 \times X + \alpha_2 \times M_o + \alpha_3 \times X \times M_o + \alpha_4 \times \mathrm{C} + r$ and the dependent variable model is: $Y = b_0 + c_1' \times X + c_2' \times M_o + c_3' \times X \times M_o + b_1 \times M_e + b_2 \times \mathrm{C} + r$, where M_e is the mediator (i.e., perceived uniqueness), X is the independent variable (i.e., user reviews variance: high vs. low), M_o is the moderator (i.e., critic reviews variance: high vs. low), C is the covariate (i.e., familiarity), and Y is the evaluation change.

In the mediator model, the interactive effect of user reviews variance and critic reviews variance on perceived uniqueness was significant (α_3 =.28, SE =.93, t = 3.04, $p < .01$). In the dependent variable model, the effect of perceived uniqueness was significant (b_1= .30, SE =.08, t = 3.94, $p < .001$), whereas the direct interactive effect of user variance and critic variance on evaluation change became marginally significant (c_3' = .19, SE =.11, t = 1.71, p = .09). Bootstrap tests showed that the interactive effect of user variance and critic variance on evaluation change was mediated by perceived uniqueness (95% Bias Corrected Confidence-Interval using 5000 bootstrap samples: .03 to .17). Thus, this experiment showed that when user reviews variance was high, high critic reviews variance amplified perceived uniqueness, which consequently led to greater evaluation change.

2.6 GENERAL DISCUSSION

2.6.1 Theoretical Implications

The effects of user reviews have received significant attention in the marketing literature. However, we still know relatively little about the nature of user reviews variance and its effect on sales. This study aims to clarify this relationship and the results from three studies using multi-context and multi-method design, leading to several theoretical implications.

First, I develop a theory about how variance of user reviews impacts sales. Specifically, I differentiate two consequences of high user reviews variance: a negative customer breadth effect and a positive customer depth effect (Fang, Palmatier, and Grewal 2011). Therefore, this study can draw our attention to a Janus-like nature of high user reviews variance: it can hurt sales by increasing perceived risk but can help sales by amplifying perceived uniqueness. This finding can deepen our understanding of the role of user reviews variance substantially.

Second, to the best of my knowledge, this is the first study to examine the interactive effects of user reviews variance and critic reviews variance. The significant interaction between user reviews variance and critic reviews variance suggests that these two sources of information should be examined together, as ignoring one could result in biased estimations of the effects of the other. By focusing on the interactive effects of user reviews variance and critic reviews variance, this study responds to the call of examining the nature of how information from multiple sources works together to affect purchasing (Kirmani and Rao 2000) and sheds light on how user reviews and critic reviews may impact important variables collectively.

Third, I also find that product quality signals can amplify the customer depth effect. The overall effects of user reviews variance can thus be negative, insignificant, or even positive, depending on which effect—the customer breadth or the customer depth effect—is stronger in different situations (e.g., whether a product is an extension or not). Therefore, my findings can reconcile conflicts in previous literature (Sun 2012; Moe and Trusov 2011; Zhu and Zhang 2010). Besides, this study, along with others (Basuroy, Desai, and Talukdar 2006), provides insights about how online word-of-mouth interacts with other product quality signals in firms' control (e.g., product cost) to affect sales.

2.6.2 Managerial Implications

This study provides several suggestions about how to manage user reviews. Although high user reviews variance decreases the potential size of a market, it is not necessarily harmful for sales if it can foster strong perceived uniqueness and purchase intentions from its niche customers. At the same time, managers should signal product quality through cues such as its cost and/or product type to strengthen the customer depth effect. My finding of the potential dominance of the positive customer depth effect suggests that having a few customers who love you could be more financially beneficial than attracting a huge number of potential customers who merely like you (Clemons, Gao, and Hitt 2006). In other words, managers need to understand that user reviews variance can have influences in two opposite directions, so firms need to assess its overall effects rather than its impacts in any single aspect. For example, managers may want to know that low user reviews variance may generate awareness among a broad range of customers, but it also could decrease the loyalty of niche market customers by diluting product uniqueness.

In addition, a side-finding of this research is that the main effects of critic reviews variance and valence are either insignificant or much weaker than the corresponding effects of user reviews. This could be explained by the similarity-attraction effect that a person (i.e., a potential buyer) is more likely to be persuaded by the other party who is similar to him/her than (i.e., a prior buyer) if the other party is not similar (i.e., a critic) (Byrne, Griffitt, and Stefaniak 1967). My finding seems to suggest that managers need to pay special attention to user reviews in the online marketing contexts, although they certainly do not want to ignore critic reviews.

Furthermore, although managers might not be able to manipulate reviews variance, they can decide whether to publicize or emphasize this information. Specifically, if user reviews demonstrate low variance, the firm should (1) disclose the variance information to consumers, (2) target the product to a mass market, (3) emphasize the low risk of the product, and (4) set up customer performance metrics to induce broad customer awareness and interests. If, however, user reviews demonstrate high variance, the firm has at least two alternative solutions, depending on the critic reviews variance. If critic reviews variance is low, the firm should try to eliminate the uncertainty and risk perceived by consumers. By contrast, if it is high, the firm may (1) target a niche market with relatively high-risk tolerance and need for uniqueness, (2) emphasize the uniqueness of the product, and (3) focus on a key performance index to generate deep customer interests. I thus propose a customer relationship management aspect of online review activities.

2.6.3 Limitations and Further Research

This study has several limitations. First, I used secondary data about movies and digital cameras to test my hypotheses. Zhu and Zhang (2010) find that other product features moderate the impact of online reviews on sales, so using data from additional industries to test my key conjectures would be desirable. Second, the operationalization of product extension may not be ideal in Study 2. According to my conceptualization, whether a product is an extension should be a default-independent signal of product quality (Kirmani and Rao 2000; Basuroy, Desai, and Talukdar 2006). In the digital camera industry, this may not be the case if developing a subsequent model is more desirable for firms than developing a totally new model because of lower risk involved in the former case. This may account for why I do not find a significant result for H4 in Study 2.

In addition to addressing these limitations, further studies can pursue several directions. First, future studies can examine potential moderating effects of other signals such as brand reputation. Consumers might infer product quality from brand reputation, so brand reputation may amplify the customer depth effect and increase sales. Second, future studies can look into text descriptions of user reviews to identify the sources of variance. For example, using text-mining methodology, future studies can explore whether such variances come from one particular product attribute or across different product attributes, and how they differentially affect product sales. Third, future studies may focus on the nature of interaction between multiple signals of product quality and give us a more complete understanding of when they strengthen one another’s effects and when they suppress one another’s effects.

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APPENDIX

	Model A	Model B	Model C	Model D	Model E	Model F	Model G
Image quality	75	80	80	80	75	85	80
Widest angle	80	80	75	85	85	80	75
Battery life	85	80	85	75	80	75	80

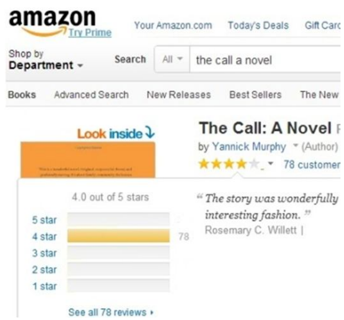
High competition and GAI design condition

	Model A	Model B	Model C
Image quality	75	90	80
Widest angle	80	75	75
Battery life	85	75	85

Low competition and DAD design condition

Figure A1 Manipulation of competition intensity and attribute design in Study 1, Chapter 1

Low user reviews variance



High user reviews variance

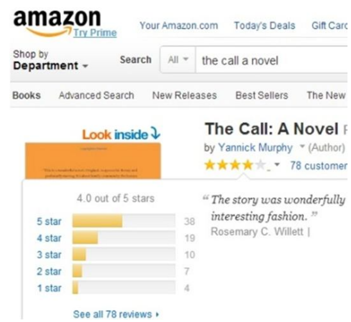


Figure A2 User reviews variance information presented to participants in Study 3, Chapter 2