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THE EFFECT OF ONLINE CONSUMER REVIEWS ON NEW PRODUCT SALES: A STUDY OF AMAZON.COM

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THE EFFECT OF ONLINE CONSUMER REVIEWS ON NEW PRODUCT SALES: A STUDY OF AMAZON.COM

by

GUO Xiaoning

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ABSTRACT

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In recent years, online word-of-mouth (WOM) communication in the form of online consumer reviews has become a major information source for consumers planning to purchase a new product. With the help of online reviews, consumers can access diverse opinions from others who have bought or used the new products before making their purchase decisions. This study compares the impact of online reviews on the sales of two types of new products (experience vs. search products) over time, in terms of the volume and valence of online consumer reviews. Using the data collected from Amazon.com over a period of nine months, we find that the volume of online consumer reviews has a greater effect on the new product sales in the late stage of product life cycle (PLC) than in the early stage of PLC. Moreover, the effect of valence of online consumer reviews is greater than that of volume of online consumer reviews. Online negative consumer reviews affect new product sales more than online positive consumer review, but not in a negative way. The results also indicate that the volume and valence of online consumer reviews have greater impact on experience products than search products. The findings suggest that online consumer reviews provide a meaningful decision aid to consumers planning to purchase new products and that online WOM gains momentum over time and significantly affects the sales of new products beyond the initial period. Practitioners need to pay greater attention to online WOM, devise suitable marketing strategies, and promote consumer advocacy to generate positive reviews when they launch new products. They may also incorporate the valuable consumer feedback in the development of new products.

DECLARATION

I declare that this is an original work based primarily on my own research, and I warrant that all citations of pervious research, published or unpublished, have been duly acknowledged.

GUO XIAONING

Date:

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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CHAPTER 1. INTRODUCTION

1.1 Rationale

With the development of e-commerce, the Internet has emerged as an important channel for marketing new products to consumers, and it has become the mainstay of electronic commerce strategies of a rapidly growing number of organizations (Subramaniam et al. 2000). Meanwhile, consumers are often confronted with new products, benefits and costs of which are not fully known to them before purchase. Although consumers can learn about the products by trying them, by doing so, they bear the risk that the experience will be negative. Instead, consumers would like to wait and observe whether other customers like the products and what consumers say about new products (McFadden and Train 1996).

In recent years, online WOM communication in the form of online consumer reviews has become a major informational source for consumers and practitioners (Hu et al. 2008). With the help of online consumer reviews, consumers can search much information online to access diverse opinions from different people who have bought or used the new products, and can make reasonable decisions by themselves. For example, a survey of Bizrate.com found that 44% of users consulted opinion sites prior to making a purchase (Piller 1999). This survey also found that 59% of respondents considered consumer-generated reviews to be more valuable than expert reviews. A recent survey of DoubleClick(2004) also finds that WOM plays a very important role in consumers' purchasing process for many types of products and for some goods, such as electronics and home products, product review websites outrank all other media in influencing customer decisions. As these results suggest, managers are interested in online WOM because it is often an important driver of consumer behavior, such as the adoption of a new technology, the decision to watch a TV show, or the choice of which laptop to purchase. Therefore, online WOM is important source of information for new products.

On the one hand, online consumer reviews provide a good opportunity for practitioners to promote new products. Because online WOM is regarded as a free advertising and is accessible to numerous people and consumers trust online consumer reviews, positive reviews can increase consumer demand for products (Reinstein and Snyder 2005). Similarly, Chevalier and Mayzlin (2006) also show that practitioners can provide promotional reviews on the Internet to increase profitability. On the other hand, consumers may prefer to rely on WOM information rather than advertising information about products (Herr et al. 1991). This may be because WOM information, as compared with marketer-provided attribute information or advertisements, is more vivid (Herr et al. 1991), easier to use, or perceived as more trustworthy because it is based on others' experiences (Smith 1993). Therefore, consumers are willing to use online WOM to make decision about new products.

Recognizing the significant value of online consumer reviews as a source of information for potential customers, e-marketers enable and encourage consumers to post product reviews and opinions on their e-retailer sites (Chevalier and Mayzlin 2006; Tedeschi 1999; Yang and Peterson 2003; Bart et al. 2005). A consumer looking for a book at Amzon.com, for example, is offered not only the editorial review typically printed on the book's cover jacket but also ratings and comments by fellow consumers who have read the book. Amazon has eliminated its entire budget for television and general-purpose print advertising since it believes that its consumers trust other consumers' opinions more than they do traditional advertising, and that such online WOM is thus more effective in influencing consumer behavior (Thompson 2003). Although books may have been one of the first categories to inspire consumer reviews on the Web, Amazon.com dedicates itself to online WOM across a wide variety of product categories, including electronics and video games.

Noticing these changes, many researchers have begun to investigate the relationship between online consumer reviews and new product sales, and found a positive relationship between the mean of online consumer review scores and new product sales (Chevalier and Goolsbee 2003; Godes and Mayzlin 2004; Chevalier and Mayzlin 2006). However, some questions remain unaddressed. First, which attribute of online consumer reviews is more important for new product sales, volume or valence? Second, is the effect of online positive consumer reviews and negative consumer reviews on new product sales different? Third, is the effect of online consumer review different for the sales of new search products versus those of new experience products? Fourth, do online consumer reviews affect new product sales more in the late stage of PLC than in the early stage of PLC? We conduct a longitudinal study on the effect of online WOM on new product sales to address these issues.

1.2 Purpose of the Study

This research examines the effect of online consumer reviews on new product sales, in terms of types of products, volume and valence of online consumer reviews and temporal effect. The first objective is to compare the effect of different measures of online WOM on new product sales. The second objective is to provide a better understanding of the effect of online positive consumer reviews and online negative consumer reviews on new product sales. The third objective is to compare the effect of online consumer reviews on sales of different types of new products, i.e. search vs. experience products. The fourth objective is to compare the effect of online WOM in the different stage of PLC.

1.3 Significance of Study

From a theoretical perspective, this study makes three contributions. First, this study first compares the impact of online consumer reviews on sales of different types of new products so that it gives us greater insight into the effect of online consumer reviews of different products on sales. Second, this study compares the effect of online positive consumer reviews with that of online negative consumer reviews on new product sales so that we have greater understanding of the effect of valence of online consumer reviews on new product sales. Third, this study compares the different measures of online consumer reviews with respect to their effects on new product sales. Fourth, this study tests several hypotheses based on the Innovation Adoption Theory in online environment.

From a practical perspective, it is important for practitioners to recognize the importance of online consumer reviews as online WOM. Second, according to online consumer reviews, practitioners can develop more suitable marketing strategies and promote consumer advocacy to create positive reviews when they launch new products. Third, this study provides suggestions for manufacturers to incorporate consumer feedback in further development of new products.

1.4 Organization of the Thesis

This thesis is organized into six chapters. A brief description of each chapter is as follows. Chapter 2 reviews significant existing literature and related theories about the relationship between online and offline WOM and new product sales. Chapter 3 presents theoretical framework, proposes the main hypotheses and provides corresponding explanations for each hypothesis. Chapter 4 discusses the operationalization of variables, data collection method, and analytical methods for testing hypotheses. Chapter 5 presents the results of the statistical analyses of data. All findings relevant to the study's hypotheses are presented in appropriate tables and figures. Chapter 6 concludes with a discussion of the findings, their theoretical and managerial implications, limitations and suggestions for future works.

CHAPTER2. LITERATURE REVIEW

The purpose of this chapter is to discuss the background of this study and review academic literature in order to provide a basis for viewing this study's results in relation to previous findings.

2.1 Word of Mouth

One of the earliest researchers on WOM was Arndt (1967) defined it as oral, person to person communication between a receiver and communicator and the receiver is perceived as non-commercial with respect to a brand, product or service. However, the advent of internet has brought new realization for both practitioners and consumers the way they use to pass or receive messages regarding the products and services, which introduced new platform for traditional WOM communication (Datta et al. 2005; Granitz and Ward 1996). Online communities allow opinions of a single individual to instantly reach thousands, or even millions of other people, and affect other consumers' decision making about products or services. Researchers find a new way to measure WOM and further investigate the effect of WOM in many fields. Practitioners also observe the effect of WOM on sales of products and adjust the marketing strategies in time.

2.1.1 The Concept of Offline and Online WOM

Offline WOM has been described as the "world's most effective, yet least understood marketing strategy" (Misner 1994). In the marketing context, it is the informal exchange of positive and negative information between individuals about a particular product or service. Negative WOM has been documented to spread quicker than positive WOM, making it "a fearful phenomenon to practitioners who cannot grant 100% customer satisfaction, and a two-edged sword as informal discussions among consumers can make or break a product" (Helm 2000). To further support the power of WOM, Grewal et al. (2003) describe how it "forms the basis of interpersonal communications and significantly influences product evaluations and purchase decisions" and that "WOM has been shown to be more powerful than printed information because WOM information is considered to be more credible".

Online WOM is basically the extension of offline WOM on the Internet. It is defined as "any positive or negative statement made by potential, actual or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (Hennig-Thurau 2004). Various websites, such as, Epinions.com, Bizrate.com, Ciao.com, and Dooyoo.com all provide forums where consumers can discuss and rate various products and services, illustrating the power of the exchange of communication in the online environment.

2.1.2 Offline versus Online WOM

Compared with offline WOM, online WOM has several distinctive features that have been discussed in the existing literature.

Social Ties: As Bickart and Schindler (2001) argued, typical offline WOM communication consists of spoken words exchanged with one friend or relative in a face-to-face situation. By contrast, online WOM usually involves personal experiences and opinions transmitted through the written word. An advantage of the written word is that people can seek information at their own pace. Writing may also transmit the information in a more intact manner and make the information appear more formal. According to Marshall McLuhan (as cited in Griffin 2003), written communication is also more logical than oral communication, as letter follows letter in an orderly line in writing, and logic is modeled on that step-by-step linear progression. The new media technology, internet, has changed the form of classic interpersonal communication (sender-message-receiver) by introducing a new form of communicator, a forwarder or transmitter (Cathcart and Gumpert 1986).

Unprecedented Scalability and Speed of Diffusion: Compared to offline WOM, online WOM is more influential due to its speed, convenience, one-to-many reach, and its absence of face-to-face human pressure (Phelps et al. 2004). Moreover, by using search engines, one can seek out the opinion of strangers. This seldom happens in conventional interpersonal context where opinion providers are embedded in social networks and well-known people may be more credible. This escalation in audience is changing the dynamics of many industries in which WOM has traditionally played an important role. For example, the entertainment industry has found that the rapid spread of WOM is shrinking the life cycles of its products and causing it to rethink its pre-and post-launch marketing strategies (Munoz 2003). In fact, movies are seeing much more rapid change in revenues between the opening weekend and second weekend, suggesting that public opinion is spreading faster.

Persistence and Measurability: In offline settings, WOM disappears into the air. In online settings, traces of WOM can be found in many publicly available Internet forums, such as review sites, discussion groups, chat rooms, and web blogs. This public data provide organizations with the ability to quickly and accurately measure WOM as it happens by mining information available on Internet forums (Dellarocas et al. 2004).

2.2 The Impact of Offline WOM on Sales

2.2.1 Traditional Measurement Techniques

Traditional attempts to measure WOM are based on three principal techniques: inference, surveys and controlled experiments. Examples of the first technique include Foster and Rosenzweig (1995) in which the farmers in the dataset were never explicitly asked about their WOM behavior. Instead, by comparing across villages, the researchers assume that "learning spillovers" take place within villages at a higher rate than they do across villages. Similarly, Reingen et al. (1984) infer the presence of interpersonal communication by comparing women who live in the same house with those that do not. The presumption is that those that live in closer proximity are more likely to exchange information with each other. Finally, Bass (1969) and those that have extended his model also infer WOM from other data. In these models, the coefficient of imitation (or coefficient of internal influence) is estimated using aggregate-level sales data.

Surveys remain the most popular method to study WOM. Bowman and Narayandas (2001), Brown and Reingen (1987), Reingen and Kernan (1986) and Richins (1983) all base their analyses on proprietary surveys designed to test a specific hypothesis. Van den Bulte and Lilien (2001) and Anderson (1998) draw on the existence of survey-based data that were prepared for other, more general, purposes. The attraction of the survey in this context is precisely that one is able to ask the direct question, "Did you tell somebody about X?" In some cases, like Bowman and Narayandas (2001), one might even ask, "How many did you tell?" Additionally, some researchers have found it useful to design and use surveys to map out social networks. For example, Reingen and Kernan (1986) used surveys to map out the entire social network comprised of the customers of a piano tuner. With this, they were able to understand which people played particularly important roles in the referral process. Brown and Reingen (1987) did so for piano teachers. Similarly, the dataset used by Van den Bulte and Lilien (2001) contained data for each physician about the other physicians with whom he or she discussed medical practices and from whom he or she sought advice.

Laboratory experiment is another popular method for inferring properties of WOM (Borgida and Nisbett 1977; Herr et al. 1991 as two representative examples of a large literature). In the Borgida and Nisbett experiment, college students received either extensive or detailed course evaluations based on ratings from a large sample of students or brief, face-to-face, course comments from a single individual. In the Herr et al. experiment, they asked students to hear that another student's father had either a good or a bad experience with his car's reliability to test the students' impressions of that brand. However, the issue with experiments is the extent to which properties identified in a controlled setting generalize to larger, real-world settings.

2.2.2 The Impact of Offline WOM on Sales

From a theoretical perspective, there exists ample support for the idea that WOM communications may in some cases impact a firm's sales. The early studies of learning from others provide evidence that offline WOM communication may affect others' decision in different social contexts (McFadden and Train 1996). Smallwood and Conlisk (1979) show that a product may capture the entire market regardless of its quality through some type of learning process. Banerjee (1993) presents two models that suggest that people are influenced by others' opinions. In fact, rational agents may ignore their own private information in favor of information inferred from others' actions. This may lead to "herding" in which all agents select the same action, which at times may be suboptimal. A similar context is analyzed by Bikhchandani et al. (1991). An important implication of the latter group's work is that the introduction of new information can cause discontinuous shifts in the actions of the agents. This may explain fads and bubbles. In addition, Kirman (1993) demonstrated a similar result that learning from others can cause a significant differentiation in market share between two products with the same quality.

The results about the impact of offline WOM on sales are mixed. Bass (1969) specifies a model of new product diffusion that explicitly incorporates interpersonal communication. He includes a parameter q: the coefficient of imitation." Due to saturation effects, his model assumes that the impact of offline WOM communication on adoption increases with time early in the product's life cycle and then decreases with time later on. This model has been shown to have some success in predicting the growth path of new products based on just a small number of data points. It is important to note that offline WOM is never explicitly measured in the estimation of this model, which is accomplished solely with an aggregate time series of sales data. He also identifies offline WOM as the primary diver in the diffusion of innovations. Reingen et al. (1984) conduct a survey of the members of a sorority in which they measure brand preference congruity as a function of their residential location. Specifically, some of the women lived in the sorority house and others did not. They found that those that lived together had more congruent brand preferences than those that did not. Presumably, those that lived together had more opportunities for interaction and thus offline WOM communication was more prevalent. Foster and Rosenzweig (1995) performed a similar study in a very different context. They investigate the adoption of high-yield varieties (HYV) of seeds among Indian farmers. They found that the profitability of farmers employing the HYV's was significantly higher as the overall adoption rate of the village increased. They interpret this as a learning spillover in that the more experienced one's neighbors become with a new technology, the better one is at employing it. Again, the presumption here is that significant interpersonal communication at the village level facilitates the flow of information regarding the new technology. They also present evidence that offline WOM has a positive but small effect on the farmers' rate of adoption of the new HYV's. Katz and Lazarsfeld (1955) find that offline WOM plays the most important role in influencing the purchase of household goods.

However, Van Den Bulte and Lilien (2001a) cast doubt on the role of offline WOM as a sales driver. They revisit the analysis by Coleman et al. (1966) who used offline WOM to explain adoption of tetracycline among physicians. The authors argue that the latter erred in their conclusion that social contagion was the driving factor behind physicians' adoption of the new product under analysis: tetracycline. By specifying the information available to the physicians as well as their social networks, the authors show that marketing effort, and not interpersonal communication, plays a dominant role in physicians' adoption decision. In Van de Bulte and Lilien (2001b), the same authors decompose the adoption process into an awareness phase and an evaluation/ final adoption phase. In this model, they find evidence of social contagion.

2.3 The Impact of Online WOM on Sales

2.3.1 The Form of Online WOM

The Internet provides various ways to obtain product-related information from consumers (Hennig-Thurau and Walsh 2004). In online environments, consumers share their experiences, opinions, and knowledge with others via chat room, newsgroup, and electronic consumer forum.

(1) Chat room: It allows "conversations" in type, and soon voice conversations will be more common. All those conversing are logged on at once and hear each other's questions and answers.

(2) Newsgroup: Once you "subscribe," you receive e-mail message posted for all list members. This form of communication may also be called a "lisery."

(3) Electronic consumer forum: It allows any visitor to access brand information, users' reviews, and aggregated ratings from users. This broader term encompasses bulletin boards, an electronic equivalent of a site on a wall for "postings."

In an electronic consumer forum, WOM is commonly articulated in the form of online consumer reviews. Typically, reviews consist of text that describes the good being evaluated, and ratings that have a numerical score that evaluates the good. Ratings usually range from a score of 0 to 5, although this varies quite a bit from website to website. This study focuses on electronic consumer forum in terms of online consumer reviews.

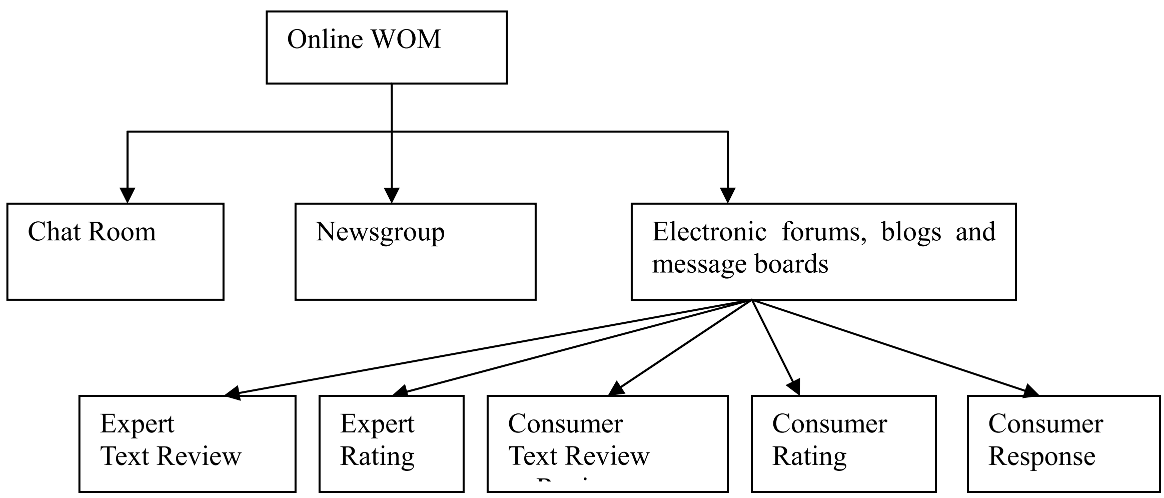


Figure1: The Form of Online WOM

2.3.2 Three Attributes of Online WOM

The advent of the Internet introduced a new technique for measuring WOM: directly through Usenet groups and feedback forums. The majority of past research on online WOM has focused on the use of it as a revenue-forecasting tool. Three metrics of online WOM have received particular attention in this context: volume, valence, and dispersion. The rationale behind measuring volume, or the number of online messages posted on a topic, is that the more consumers discuss a product, the higher the chance that other consumers will become aware of it. Liu (2006) found that the volume of messages posted on Internet message boards about upcoming and newly released movies was a good predictor of their box office success. The theory behind valence, or the fraction of positive and negative opinions in the mix of messages, is that, in addition to building awareness, WOM carries important information about a product's quality. Dellarocas et al. (2005) found that the valance of online ratings posted during a movie's opening weekend was the most important predictor of that movie's revenue trajectory in subsequent weeks. The reason behind measuring dispersion, or the spread of communication, is that WOM spreads quickly within communities, but slowly across them (Granovetter 1973). Godes and Mayzlin (2004) found that the dispersion of conversation about weekly TV shows across Internet communities had positive correlation with the evolution of viewership of these shows.

Although dispersion is one of most important measures of WOM in the literature, because this measure is difficult to construct from the current data, this study focuses on the volume to measure the total amount of WOM interactions, and valence to capture the nature of WOM messages (i.e. whether they are positive or negative).

2.3.3 The Impact of Online WOM on Sales

With the emergence of online consumer reviews, some scholars are interested in the effect of online consumer reviews on new product sales and find that online WOM influences new product sales. Although the books used in such studies are not new products, yet other products scholars used are new products, such as new TV shows, new movies, and new types of beers. Chatterjee (2001) used a survey to examine the impact of negative online user reviews. The results indicate that the use of online WOM information depends on consumers' intention of online purchasing. Consumers who are more familiar with a specific retailer are less likely affected by the negative reviews. Dellarocas et al. (2004) employed a modified Bass Diffusion Model to study the effects of online user reviews to forecast movie revenues. They find that online reviews of movies can be a good proxy for WOM and can be useful in revenue forecasting. Godes and Mayzlin (2004) use newsgroups as a measure of WOM to study TV show ratings. They find that online WOM can affect people to view new TV shows.

However, the scholars have different opinions about the role of volume, valence and dispersion of online reviews on product sales. Which aspect of online WOM influences sales has not been decided. Some scholars think the valence in form of ratings influences the product sales. Zhang et al. (2004) developed a simple linear regression model showing that aggregate weekly user review ratings are positively correlated with the change of movie revenues. Chevalier and Mayzlin (2006) find that improvement in a book's average ratings leads to an increase in relative sales at that site. Dellarocas et al. (2004) use a Bass diffusion model to examine how user ratings posted in the opening week help explain the two Bass parameters (p= the external influence factor, and q= the internal influence factor), which are estimated from the box office history of a movie sample. They find that the volume of the first week's user ratings and their density (defined as a ratio between the volume of ratings and the first week's box office revenue), but not the numerical value of these ratings, are useful in explaining p. Nevertheless, the value of user ratings becomes a significant explanatory variable for q. However, some scholars hold a different opinion about it, considering other measures, such as volume or dispersion of online reviews, influence product sales. Duan et al. (2005) use similar user-ratings data but focus on the correlation between the daily measures of these ratings and the daily box office revenue in the first two weeks. They find that user ratings have no explanatory power for box office revenue, but the volume of ratings does. Godes and Mayzline (2004) use newsgroups as a measure of WOM to study TV show ratings. They find that, whereas the dispersion of conversations among different newsgroups has significant explanatory power, the associated volume of postings does not (Table 1). Overall, although researchers recognize the role of online WOM in consumers' purchase decisions, the findings on the effect of different measures of online WOM on new product sales have been inconsistent and inconclusive.

Table 1: Literatures in Online Consumer Reviews

Author	Year	IV	DV	Research Findings
Chen, Fay and Wang	2003	• Product price • Product quality • Emotional response	• The number of posting	They find product quality and attractiveness design has a positive impact on generating positive online reviews; consumers are less sensitive to the product price; online consumer reviews are reliable.
Chen and Xie	2004	• The percentage of consumers' who vote positive ratings • Length of time when products launch into the market	• Whether to offer consumer reviews	They construct an analytical model on how this new information channel influences a monopoly's sales. They find that recommendations are positively associated with sales, while consumer ratings are not found to be related to sales.
Godes and Mayzline	2004	• The volume of WOM • The dispersion of WOM	• Further sales	They use newsgroups as a measure of WOM to study TV show ratings. They find that whereas the dispersion of conversations among different newsgroups has significant explanatory power, the associated volume of postings does not.
Dellarocas, Awad and Zhang	2004	• Online movie rating	• Motion picture revenues	They find that online reviews of movies can be a good proxy for WOM and can be useful in revenue forecasting.
Li and Hitt	2004	• Book ratings	• Book sales	They find that online ratings for a product decrease over time, suggesting self-selection of reviewers.
Duan, Gu and Whinston	2005	• The volume of WOM • User review ratings	• Box office revenues	They find that user ratings have no explanatory power for box office revenue, but the volume of rating does.

Table 1: Literatures in Online Consumer Reviews (continued)

Author	Year	IV	DV	Research Findings
Dellarocas Awad and Zhang	2005	• Production, Marketing and Availability • Release strategy • MPAA Ratings • Genre • Professional Critics • User Ratings	• Future revenues	They find the valence of user ratings to be the most significant explanatory variable; the gender diversity of online raters is also significant; The user ratings are more influential in predicting future revenues than average professional critic ratings. (Valence: the arithmetic mean of posted ratings during the same period.)
Dellarocas Awad and Zhang	2005	• The average valence of online ratings	• Early opening weekend' box office revenue	They find that the propensity to rate a movie online is positively related to that movie's marketing expenditures; public disagreement about a movie's quality is associated with a high propensity to rate it online; people have a higher propensity to post online ratings for less popular/ less widely-released movies.
Chevalier and Mayzlin	2006	• Review ratings • Review length	• Book sales	They find that improvement in a book's average ratings leads to an increase in relative sales at that site. This finding is contradicted to that of Chen and Xie (2004).
Delarocas and Narayan	2006	• Marketing budget • Average rating • The number of screen • Critic ratings	• The propensity to postpurchase online WOM	They examine what motivates consumers to post reviews for different kinds of movies. They find that most consumers rate movies very high or very low, resulting in a bimodal, U-shaped histogram.

Table 1: Literatures in Online Consumer Reviews (continued)

Author	Year	IV	DV	Research Findings
Hu and Zhang	2006	• Average Rating • Number of reviews • Sales rank	• Further Sales	They find that most online reviews on Amazon.com are distributed bimodally and provide conditions under which these ratings will converge to the real product quality.
Gao, Gu and Lin	2006	• Consumer review	• Recent consumer reviews • Professional reviews • Community consensus	They find that consumer reviews are heavily influenced by public opinions, such as consensus ratings, recent consumer ratings and professional ratings.
Liu	2006	• Volume of WOM • Valence of WOM	• Box office sales	They find that most of this explanatory power comes from the volume of WOM and not from its valence, as measured by the percentage of positive and negative messages; WOM activities are the most active during the movie's prerelease and opening week and audience holds relatively high expectations before release but become more critical in the opening week.
Clemons, Gao and Hitt	2006	• Average of high/low-end reviews • Dispersion of ratings	• Sales growth	They find that the variance of ratings and the strength of the most positive quartile of reviews play a significant role in determining which new products grow fastest in the market-place.

Table 1: Literatures in Online Consumer Reviews (continued)

Author	Year	IV	DV	Research Findings
Un, Youn, Wu and Kuntarapo rn	2006	• Innovativeness • Individual internet usage • Music involvement • Internet Social connection	• Online opinion leadership • Online opinion seeking • Online forwarding • Online chatting	They find that identified innovativeness, internet usage, and internet social connection as significant predictors of online WOM, and online forwarding and online chatting as behavioral consequences of online WOM. Music involvement is found not to be significantly related to online WOM.
Hu, Liu and Zhang	2007	• Reviewer quality • Reviewer exposure • Product coverage	• Immediate sales	They find that reviewer quality and product coverage are positively related to the immediate sales of products; the impact of online review on sales is moderated by the information environment of products; the impact of reviewer exposure and product coverage on sales is moderated by the innovation level of review signal.
Amblee and Bui	2007	Brand Reputation Complementary goods reputation	• Additional review posted • Sales	They find that not all reviews impacted sales and micro-product with high(low) brand and complementary goods reputations are more (less) likely to have reviews posted to them in the future. The sales of a digital micro-product with a high brand and complementary goods reputation will be affected by the addition of a review, while those of a digital micro-product with a low brand and complementary goods reputation will be not affected by the addition of a review.

2.3.4. Theory Perspective

The success of vital marketing and WOM can best be explained using the Diffusion of Innovations Theory, which refers to the dissemination of information, abstract ideas, concepts, and practices within a particular group. The dynamics may vary in size from a group of close peers, to an organization or company, to even an entire cultural or social system (Rogers, 1995; Wejnert, 2002). Among the numerous studies, two major models, namely Bass model and Rogers's model, have received consideration attention.

The Bass Model: The best-known first-purchase diffusion model of new product diffusion in marketing is Bass model (1969). It represents the impact of communication efforts about a new product, whether those efforts are external in nature, such as mass advertising, or more internal in nature, such as WOM communication or observation and imitation. The model assumes that there are differences among customers in terms of how innovative they are in their tendencies to adopt new products, and which types of information about a new product are most persuasive prior to adoption. When a new product is introduced, there exists uncertainty in the minds of potential adopters regarding how superior the new product is versus existing alternatives. Individuals attempt to reduce this uncertainty by acquiring information about the new product. More innovative customers tend to acquire such information via mass media and other external outlets. More imitative customers tend to acquire such information from interpersonal channels such as WOM communication and observation. The relative influence of these two basic types of customers is captured in the Bass model. Bass termed the first group "Innovators" and the second group "Imitators".

The Bass model thus assumes that new product adopters are influenced by two types of communication: mass media and interpersonal communication. In addition, it assumes that the mass media effects, which have a greater impact on innovative customers, will be greater at the outset of the product launch, whereas the interpersonal communication effects, which have a greater impact on the much larger number of imitative customers, will be greater during the later periods of the diffusion process. Innovator group is influenced only by the mass-media communication (external influence) and the imitator group is influenced only by the WOM communication (internal influence). Bass, then, developed the density function of time to adoption and cumulative fraction of adopters, and the S-shaped cumulative adoption curve (Figure 2), based on the premise: $f(t)/[1-F(t)] = p+qF(t)$ (p: the coefficients of external influence, q: the coefficient of internal influence). Drawing from the Bass's research, marketers use diffusion models to explain the pattern of cumulative adoptions across time. This process is generally described in terms of acceptance rates among influential leaders and subsequence adopters.

Figure 2 and Figure 3 are plots of the conceptual and analytical structure underlying the Bass model. As noted in Figure 2, the Bass model conceptually assumes that "Innovators" or buyers who adopt exclusively because of the mass-media communication or the external influence are present at any stage of the diffusion process. Imitators as followers are affected only by internal influence, such as WOM communication, and the effect of internal influence is greater in the late stage. Figure 3 shows the analytical structure underlying the Bass model. As depicted, the noncumulative adopter distribution peaks at time T*, which is the point of inflection of the S-shaped cumulative adoption curve. Furthermore, the adopter distribution assumes that an initial pm (a constant) level of adopters buy the product at the beginning of the diffusion process. Once initiated, the adoption process is symmetric with respect to time around the peak time T* up to 2T*. That is, the shape of the adoption curve from time T* to 2T* is the mirror image of the shape of the adoption curve from the beginning of the diffusion process up to time T* (Mahajan et al. 1990).

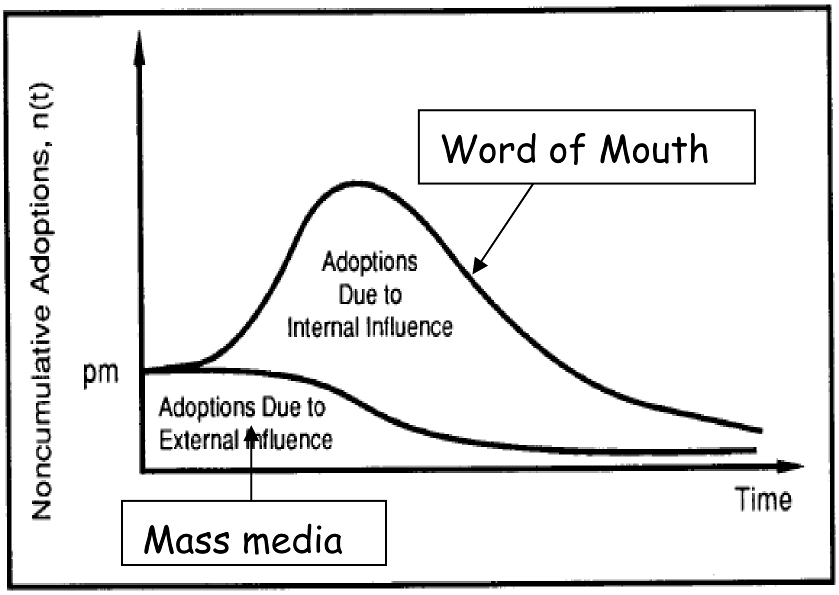


Figure2: Adoption Due to External and Internal Influences in the Bass Model

The model developed by Bass (1969) assumes that the impact of WOM communication on adoption increases with time early in the product's life cycle and decreases with time later on (Figure 2). In his model, each person is either an informer or a potential informee. Since the number of informers is constantly growing, their impact grows initially. Eventually, due to saturation effects, the number of informees gets so small that the impact of the informers necessarily diminishes. There are fewer and fewer people to tell. This model has been shown to have some success in predicting the growth path of new products based on just a small number of data points and has been used to test hypotheses related to the dynamics of innovation diffusion. In other words, this model has been shown capable of predicting the growth pattern of a wide range of new products with minimal data.

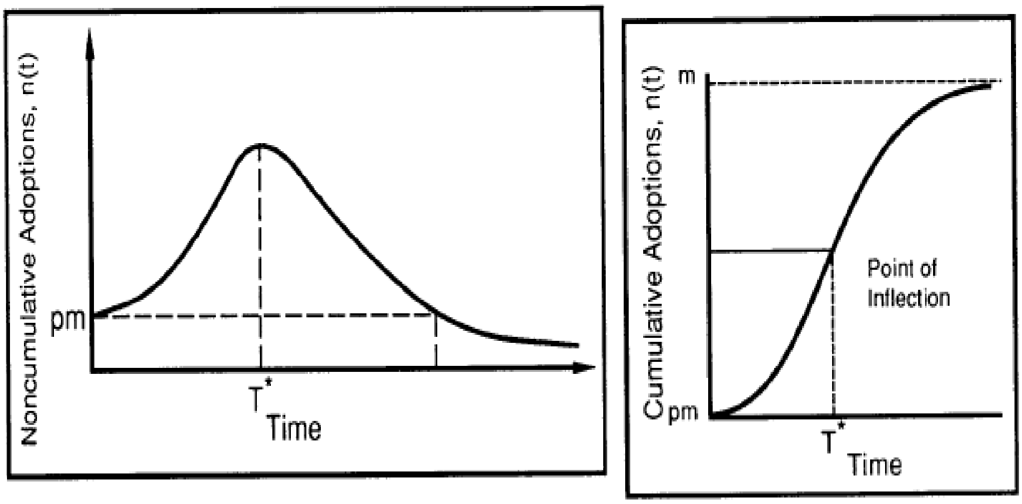


Figure 3: Analytical Structural of the Bass Model

Rogers's Model: Rogers (1983) has articulated that the adoption curve should have a normal distribution because of interpersonal interactions. Using two basic statistical parameters of the normal distribution (mean and standard deviation), Rogers has proposed an adopter categorization dividing adopters into five categories, namely, innovators, early adopters, early majority, late majority, and laggards, with 2.5%, 13.5%, 34%, 34%, and 16% of the population respectively. Later, Rogers (1995) proposed a model describing the five-stage process of decision making for innovation adoption, *knowledge, persuasion, decision, implementation*, *confirmation,* respectively.

Rogers (1995, 2003) defines innovation diffusion as a process by which an innovation is communicated through certain channels over time among the members of a social system. Given this definition, the diffusion process consists of four key elements: innovation, communication channels, time, and social system. The element of innovation concerned the attributes of the innovation and the characteristics of several categories of potential adopters. The element of communication channel is defined as "the means by which message get from one individual to another" and emphasized two types of communication process: mass media and interpersonal. While mass media communication may have created awareness, interpersonal communication by trusted peers tended to influence the actual adoption decision. The element of time is theorized as a salient variable in the adoption process. The innovation-decision period, according to Rogers, is the duration of time that is needed for the adoption process to occur. The element of social system is defined by the presence and activity of related individuals, groups or organizations who share a common goal.

In our study, we focus on the innovators and imitators in Bass model. The innovators include innovators and early adopters and, the imitators include early majority, late majority, and laggards in Rogers' model. According to Rogers Model, interpretation communication, such as WOM, is one type of communication channels, and it is very important for actual new product adoption. Online WOM in form of online consumer reviews, as a communication channel, affect innovators and imitators to adopt new products with incremental innovation in the electronic consumer forum as a social system, where people have the same goal (that is to purchase new products). According to Bass Model, in the early stage (introduction stage) of new PLC, the innovators are only affected by mass media and, after using new products, they write their comments about them. Later, the imitators read the product reviews from innovators and make decision to purchase new products or not. Therefore, beyond the early stage of PLC, online WOM plays an important role in consumers' purchasing new products.

Social Network Theory: Social network theory views social relationships in terms of nodes and ties. Nodes are the individual actors within the networks, and ties are the relationships between the actors. There can be many kinds of ties between the nodes. In its simple form, a social network is a map of all of the relevant ties between the nodes being studied. The network can also be used to determine the social capital of individual actors. These concepts are often displayed in a social network diagram, where nodes are the points and ties are the lines.

The power of social network theory stems from its difference from traditional sociological studies, which focus on the attributes of individual actors, whether they are friendly or unfriendly, smart or dumb, etc. Social network theory produces an alternative view, where the attributes of individuals are less important than their relationships and ties with other actors within the network (Haythornthwaite 1999). This approach has turned out to be useful for explaining many real-world phenomena, and usually used in the study of WOM (Brown and Reingen 1987; Bansal and Voyer 2000).

While there are many reasons to believe that WOM is often important in driving consumer actions, it is less clear which aspects of WOM are especially important. Existing literature has demonstrated that not all WOM is created equal. WOM's impact depends on who is talking to whom. Granovetter (1973) characterizes relationships as being either strong ties or week ties. He assumes that if A and B are connected by a strong tie and B and C are connected by a strong tie, then A and C must also be connected by a strong tie. We might make the further assumption that communities or groups are characterized by relatively strong ties among their members. Then a direct implication of this model is that the only connections between communities are those made along weak ties. This highlights the critical role played by weak ties in the diffusion of WOM: Any piece of information that traverses a weak, as opposed to a strong tie, it is likely to reach more people. This has the important implication that information moves quickly within communities but slowly across them. In a similar vein, the work by Kaplan et al. (1989) in mathematical bioscience shows that different patterns of contact between groups with different incidences of HIV/AIDS have different impacts on the spread of the disease. This modeling approach has been utilized in the marketing literature by Putsis et al. (1997). They find heterogeneity in mixing behavior across 10 nations. Importantly for the present study, they find greater interaction within the population of a country than between populations of different countries.

According to social network theory, the influence of offline WOM is significant in affecting the attitude and behavior of such a group (Figure 4). In the offline setting, social network just focuses on the individual-to-individual relationship (Brown et al. 2007). However, the influence of online WOM, which is much higher in both reach and frequency without time and location limitations, is greater than that of offline WOM. Within online community groups, WOM is expected to affect the attitude and behaviors of their members (Brown et al. 2007). E-commerce website can be considered as a community or social network with strong ties (e.g., registered members) and weak ties (nonmembers and passer-bys) In the online context, the actors appear to be individuals who “relate” to Web sites rather than other individuals –only occasionally engaging in individual-to-individual contact(Figure 5).

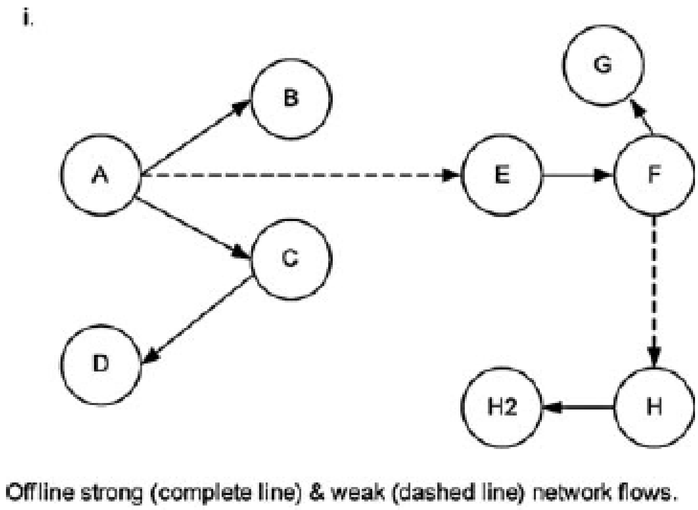


Figure 4: Offline WOM through Social Network

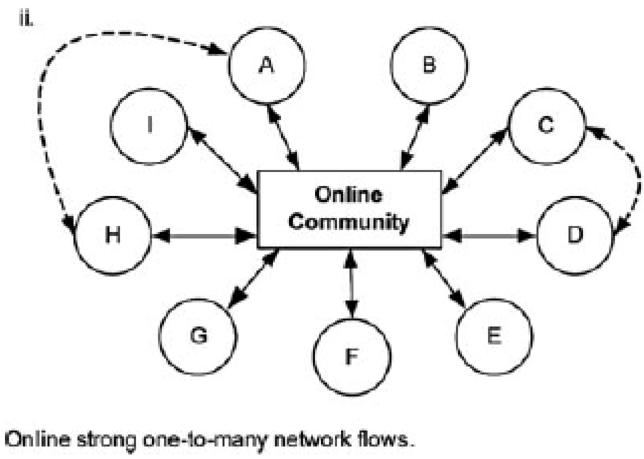


Figure 5: Online WOM within online community

Figure 4 and Figure 5 express the online social network conceptualization in comparison to offline social information flows. The model in Figure 5 suggests that a collective of individuals each contribute and receive information from an online community. However, unlike social network in the offline context, once the information is posted, the online community becomes the primary unit of relationship rather than the individual. Therefore, online WOM is more influential with one-to-many points. From the analysis above, we can see the role of online WOM is significant in influencing the consumers' decision-making.

2.4 Summary

There are three limitations of previous research. First, although previous studies have found that online WOM can influence the product sales, the results of previous studies on the explanatory power of measures have been somewhat inconsistent. Some scholars think volume of online WOM has impact on new product sales. For example, Liu (2006) studied the impact of Yahoo! Movies prerelease message board discussions on motion picture box office revenues. Somewhat surprisingly, he finds that, whereas the volume of online conversations has explanatory power, the valence does not. Duan et al. (2005) examined the relationship between daily Yahoo! Movies reviews and box office sales. They similarly find that the volume, but not the valence, of movie ratings has explanatory power. However, other scholars believe the valence, not the volume of online WOM has impact on new product sales. For instance, Chevalier and Mayzlin (2006) examined the effect of consumer reviews on relative sales of books at Amzaon.com and Barnesandnoble.com by providing the summary descriptive statistics about valence and volume of online consumer reviews. The results indicated that valence of online book reviews has explanatory power on book sales. The result is contrary to the former's opinion. Second, many scholars focus on only one type of product, such as books, movies, TV shows or beers. We have little knowledge about the differences of the effect of online WOM of different types of products on product sales. Third, the effect of valence of online WOM has been investigated recently, but there are few papers to investigate the difference between the effect of online positive and that of online negative WOM on product sales, especially for new product sales.

CHAPTER 3. HYPOTHESIS DEVELOPMENT

In this section, applying the Innovation Adoption Theory and Social Network Theory and other theories, this study proposes a theoretical framework, and then gives a more detailed explanation for each hypothesis.

3.1 Theoretical Framework

Reviewing the extant literatures on online WOM, most literature focuses on the relationship between online WOM and new product sales, but which attribute of online WOM is influential in such relationship is not clear, and more factors affecting this relationship are not yet investigated. Extending the prior studies, this study emphasizes the impact of online WOM on new product sales by examining the role of product type and the role of stage of new PLC. We investigate the effect of different measures of online WOM on new product sales, such as volume and valence. We also investigate the role of product type and stage of new PLC on new product sales to give greater insight into other factors that affect the relationship between online WOM and new product sales. Applying social network theory, we point out the important role of online WOM on consumer decision making. According to Bass model and Rogers' model, we can further see that the role of online WOM in consumers' purchasing new products, especially in the late stage of new PLC. Since we realize the role of online WOM in different stages of new PLC is different, we incorporate the stage of new PLC in our theoretical framework as a moderator of relationship between online WOM and new product sales. We also add the product type as another moderator of relationship between online WOM and new product sales because the effect of online WOM on new product sales is different with respect to different types of new products (Theories are explained in the later section). This is shown in Figure6.

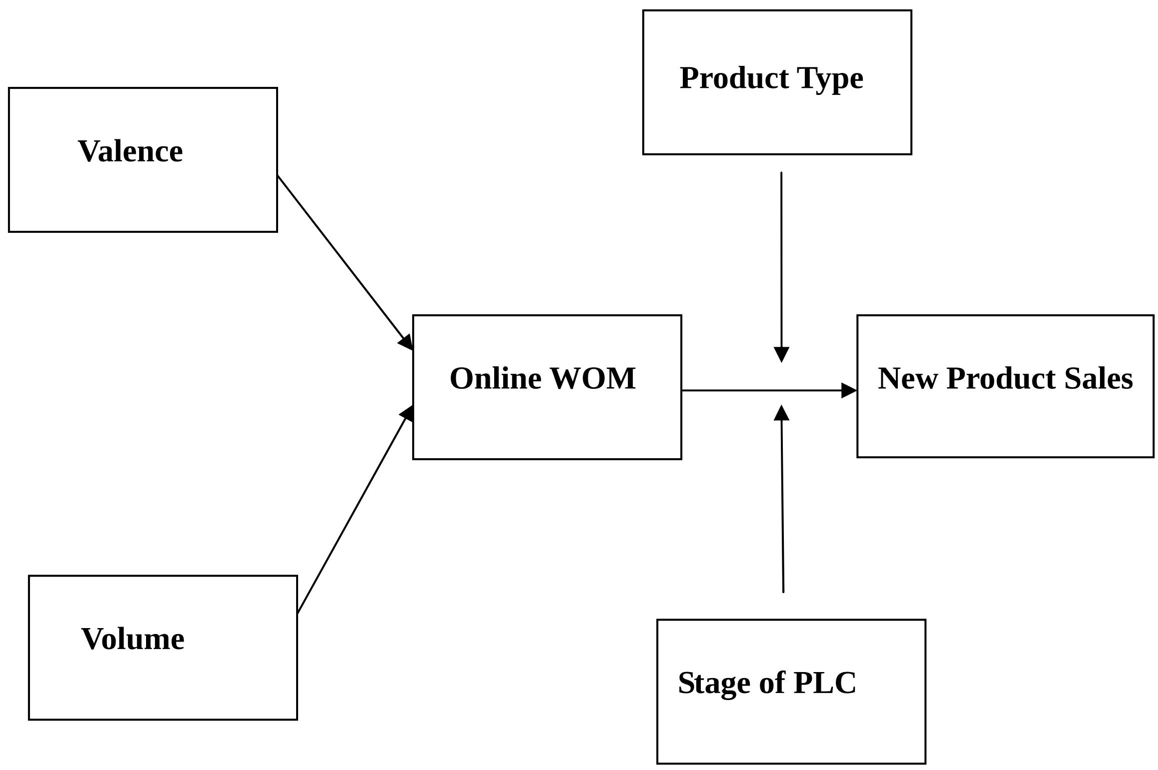


Figure 6: Theoretical Framework

3.2 Hypotheses Development

Since E-commerce is developing better and better, many companies promote their new products in online stores, such as Amazon.com. As more and more people would like to search information online and exchange their information on Internet, Internet provides a good platform for consumers to get information about new products and for companies to promote their new products. Such phenomenon triggers the interest of scholars to investigate the role of online WOM on new product sales.

Extant studies have found that the volume of WOM correlates significantly with consumer behavior and market outcome (Anderson and Salisbury 2003; Bowman and Narayandas 2001; Van den Bulte and Lilien 2001). The reason that the pure volume of WOM matters is consumer awareness. For example, Godes and Mayzlin (2004) suggest that the more conversation there is about a product, the more likely someone is to be informed about it, thus leading to greater sales. On the basis of a similar rationale, research that uses diffusion models often examines WOM by either the number of adopters (Neelamegham and Chintagunta 1999) or the interaction between the number of adopters and that of non-adopters (Zufryden 1996).

According to the Bass Model, offline WOM can influence new product sales. According to Social Network Theory, online WOM is more powerful and more reachable than offline WOM. Thus, online WOM can also influence new product sales. That's, more people who are not informed before will know about the product information and evaluations from others, and then more people will buy new products or not, when the comments are positive or negative, leading to more or less sales of new products. Thus, we posit that:

Hypothesis 1: The higher the volume of online consumer reviews, the greater impact it has on the new product sales.

Positive WOM typically gives either a direct or an indirect recommendation for product purchases. Negative WOM may involve product denigration, rumor, and private complaining. The reason valence matters is relatively straightforward; positive WOM enhances expected quality (and, thus, consumers' attitudes toward a product), whereas negative WOM reduces it (Liu 2006). Therefore, the positive reviews can be regarded as positive signals of potential gains for consumers to buy a new product, while the negative reviews can be regarded as negative signals of potential losses for consumers to buy a new product. According to prospect theory (Kahneman and Tversky 1979), when consumers make decision under risk (the result of purchase may be negative), consumers always compare the potential gains with the potential losses of this choice. Since people would like to consult information about new products online and trust the information offered by other people, and since positive comments reflect the good quality of new products and negative comments reflect the bad quality of new products, positive or negative reviews offered by other consumers can influence the consumers to make decisions about new products. Thus, the valence of online consumer reviews can influence consumers' decision, and then affect new product sales. Thus, we posit that:

Hypothesis 2: The more positive the valence of online consumer reviews, the greater positive impact it has on new product sales.

Vivid material is likely to have greater effect on judgment because vividly presented material is presumed to be more effectively processed at encoding and, therefore, is more likely than nonvivid material to be available when judgment is made (Taylor and Thompson 1982). WOM communications as vivid information have a greater impact on product judgments than less vivid information (Herr et al. 1991). In addition, highly vivid message presentations will enhance the attention paid to a communication and thus increase message persuasiveness (Mathews 1994). Therefore, WOM are more persuasive than less vivid information. Since the online WOM is more influential than offline WOM, online WOM are more persuasive than offline WOM.

Similarly, since the valence of online consumer reviews can tell more stories of new products to consumers than the volume of online consumer reviews and, it can render positive or negative information to online consumers, the valence of online consumer reviews is more vivid and more persuasive than the volume of online consumer reviews on consumer judgment. Thus, we posit that:

Hypothesis 3: The valence of online consumer reviews has greater impact on new product sales than the volume of online consumer reviews.

Prior studies find that people pay more attention to negative information than positive information. Previous research on the impression-information literature showed that when comparing negative with positive information, people placed greater weight on negative information during product assessment (Fiske 1980; Skowronski and Carlston 1989). Research in consumer information search also showed that when there is time constraint, people tend to focus more on negative information than positive information (Wright 1974) and unfavorable product ratings tended to have a greater impact on purchase intention than did favorable product ratings (Weinberger and Dillon 1980). Research in other areas of consumer behavior has found strong evidence that negative information has more value to the receiver of WOM communication than positive information, and therefore that consumers weight negative information more heavily than positive information in both judgment and decision making tasks (Ahluwalia and Shiv 1997; Feldman 1966; Kanouse and Hanson 1972; Sknowronski and Carlston 1989; Weinberger et al. 1981).

A widely accepted explanation for the impact of negative WOM is the so-called negativity bias, a psychological tendency for people to give greater diagnostic weight to negative than positive information in making evaluation (Herr et al. 1991). This widely observed negativity effect can be explained as a function of the individual's social environment. Because one's social environment contains a greater number of positive than negative cues, negative cues are perceived as counter normative (Feldman 1966; Zajonc 1968; Kanouse and Hanson 1972). Therefore, the negative cues appear, tend to attract attention and are heavily attributed to the stimulus object more than positive cues (Kanouse and Hanson 1972). Similarly, negative information is more diagnostic than positive information, because the influence of negative information assigning the target to a lower-quality class exceeds that of positive information's assigning the target to a higher-quality class (Ahluwalia and Gurhan-Canli 2000). Therefore, the effect of negative information is greater than that of positive information on consumer decision making. We believe that such effect also exists in the online environment and we posit that:

Hypothesis 4: Online negative consumer reviews have greater impact on new product sales than online positive consumer reviews.

Prior research has shown that the product type affects consumers' use of personal information sources and their influence on consumers' choices (Bearden and Etzel 1982; King and Balasubramanian 1994). According to the nature of products, products can be classified as search or experience goods, and the search/experience distinction is based on the extent to which consumers can evaluate goods or their attributes prior to purchase (Nelson 1970). Search goods, such as electronics, are products that consumers can evaluate by specific attributes before purchase. Experience goods, such as recreational services, primarily vary across consumers and are difficult to describe using specific attributes. However, given that information search cost differ across channels, a search good or attribute through one channel may be an experience good or attribute through another channel. For example, the smell of flowers can be assessed prior to purchase in a bricks-and-mortar, but not in an online, florist shop. Consequently, using this paradigm in channel-related research (e.g. in an effort to match goods to cannels) can present problems. Weathers et al. (2007) base their classification on the extent to which consumers feel they need to directly experience goods to evaluate quality. The greater the need to use one's senses to evaluate a good, the more experience qualities the good possess. The more one feels that second-hand information will allow for adequate evaluation of the good, the more search qualities the good possesses.

Since experience products are typically evaluated by affective evaluative cues (i.e., the aesthetic aspects of the product) while search goods are usually evaluated by instrumental evaluative cues (i.e., the more technical aspects or performance aspects of a product) (Ben-Sira 1980), consumers may rely more on product reviews for experience products than for search products. In support of this view, King and Balasubramanian (1994) found that consumers assessing a search product are more likely to use own-based decision-making processes than consumers assessing an experience product are, and that consumers evaluating an experience product rely more on other-based and hybrid decision-making processes than consumers assessing a search product do. Thus, we posit that:

Hypothesis 5a: The volume of online consumer reviews has greater impact on new experience product sales than new search product sales.

Hypothesis 5b: The valence of online consumer reviews has greater impact on new experience product sales than new search product sales.

Bass Model implies that, in the early stage (the introduction stage) of PLC, consumers to adopt the new products are innovators who are only affected by the external influence, such as mass media, so that the effect of mass media domains the adoption of new products in the early stage. Also, it implies that, in the late stage of PLC, the adoption of new products is increased due to the increasing number of imitators who are only affected by internal influence, such as offline WOM so that offline WOM plays a important role in new product adoption in the late stage. In other words, the external influence affects new product adoption more in the early stage of PLC, while the internal influence affects new product sales more in the late stage of PLC. Because Social Network Theory shows that online WOM is more influential than offline WOM, the role of online WOM on new product sales is greater than that of offline WOM. Therefore, online WOM also has the effect of offline WOM in the Bass model. That is, in the early stage of PLC, the mass media affects the innovators to buy new products, while, in the late stage of PLC, the online WOM affects the imitators to buy new products.

In our case, the innovators who have used or bought the new products write comments about the new products online, and later, imitators read these online consumer reviews and make decision to buy the new products or not. In the early stage of PLC, the new product sales are influenced mainly by mass media from companies, while in the late stage of PLC, the new product sales are influences mainly by online consumer reviews. Although the context in our study differs from that studied originally by Bass in that it is a repeat purchase product with a relatively low sampling cost, we still expect this theory can be applied in our context. Thus, we posit that:

Hypothesis 6: The effect of volume of online consumer reviews on the new product sales is greater in the late stage of new product life cycle than in the early stage of new product life cycle.

CHAPTER 4. RESEARCH METHODOLOGY

The purpose of this chapter is to detail the techniques used for collecting the data, which was used ultimately for testing the hypotheses related to proposed model in Chapter 3. This chapter also includes the statistical methods that were used to test these hypotheses.

4.1 Data Collection

We tracked the online consumer reviews in terms of volume and valence of reviews, sales rank data and related information of a few selected new products on a weekly basis since they are released on Amazon.com for 9 months, from August 2007 to April 2008.

4.1.1 Website Selection

The WOM data are collected from Amazon.com Inc (www.amazon.com). There are several reasons that Amazon serves as a good source of WOM of new products. First, it is one of the most popular online shopping websites and it has been well-known for its extensive customer review system. Second, it requires no access fee for either browsing or posting a message. This helps reduce any possible bias in the demographic composition of the Web site's visitors. Third, the structure of the Web site is well designed so that finding and collecting information is straightforward, thus reducing possible errors during data collection. Fourth, WOM messages are archived and indexed numerically by the dates when they are posted. Thus, it is possible to track the period to which a particular message belongs. Finally, it is convenient for us to collect product sales data by finding out the sales ranking of each product on this website.

4.1.2 Product Selection

Products are classified into two groups, that is, search product category and experience product category. In our study, we chose Electronics as search product category, and Video Games as experience product category. There are two reasons to select these products. First, in the Amazon.com, these products have many online consumer reviews so it is easy for us to collect related information. Second, these products are always used as search or experience products in papers related with product type so it is useful for us to investigate the role of product type (Weathers et.al 2007; Moon et al. 2008).

4.1.3 Variables

The variables include dependent variables, independent variables, moderating factors and control variables. Dependent variable is new product sales rank. Independent variables are volume and valence of online consumer reviews. Moderating factors include product type and stage of PLC. Control variables are product category, product subcategory, list price, promotion, other stores to provide such products, and shipping availability.

4.2 Operationalization and Measures

Online Consumer Review: Based on Chevalier and Mayzlin (2006), we used the number of reviews to measure the volume of online consumer reviews. Based on Clemons et al. (2006) and Dellarocas et al. (2007), we used the average ratings, i.e., average number of stars the reviewers assigned (on a scale of one to five stars, with five stars being the best) to capture the valence of online consumer reviews.

New Products: There are two kinds of innovation to produce new products, including incremental innovation and radical innovation. Incremental innovation is a step forward along a technology trajectory, or from the known to the unknown, with little uncertainty about outcomes and success and is generally minor improvements made by those working day to day with existing methods and technology (both process and product), responding to short term goals. Most innovations are incremental innovations. Radical innovation is launching an entirely novel product or service rather than providing improved products and services along the same lines as current ones. The uncertainty of radical innovations means that seldom do companies achieve their breakthrough goals this way, but those times that breakthrough innovation does work, the rewards can be tremendous. Radical innovation involves larger leaps of understanding, perhaps demanding a new way of seeing the whole problem, probably taking a much larger risk than most people are willing to take. There is often considerable uncertainty about future outcomes. There may be considerable opposition to the proposal and questions about the ethics, practicality or cost of the proposal may be raised. Radical innovation involves considerable change in basic technologies and methods, created by those working outside the mainstream industry and outside the existing paradigms. Because most of new products are ones with incremental innovations, we used new products with incremental innovations in our study. We define the products newly released on Amazon.com as new products.

New Product Sales: Amazon.com does not provide the actual sales numbers for its products. Instead, we use the Sales Rank of the products selected within Amazon.com as a proxy of actual sales. The sales rank is inversely related to sales. That means the top-selling product at that site has a sales rank of one, and the lower sellers are assigned higher sequential ranks. According to Chevalier and Goolsbee (2003), the relationship between the sales rank and the actual volume of book sales on Amazon can be approximately describe by: $\ln [Sales] = \beta 0 - \beta 1 * \ln [SalesRank]$. Schnapp and Allwine (2001) and Rosenthal (2005) also find that the relationship between ln (sales) and ln (ranks) is approximately linear. This finding suggests that in lieu of sales data, log rank is the appropriate dependent variable. Because sales rank is a log linear function of sales with a negative slope, we used –Log [SalesRank] as the dependent variable.

Moderating Factors: For stage of PLC, in the cross-sectional analysis, we used 0 for early stage of PLC and 1 for late stage of PLC, but in the panel data analysis, we used ageweek to measure the stage. Ageweek is not calendar week, but actual week since new product is released. For product type, we used 0 for search product category and 1 for experience product category.

Control Variables: We included the product subcategories to control for the product subcategory variations. For example, for search products, subcategories are electronics accessories, cameras, Televisions, MP3 players, computers, office electronics, GPS, equalizer and optics; for experience products, subcategories are playstations3, Xbox360, Nintendo Will, Playstation2, Xbox, GameCube, Mac Games, Sony PSP, Nintendo DS, Game Boy Advance. We used list price to control price variation between different products. We used price promotion to control the effect of promotion on product sales. Sometimes, Amozon.com provides other stores to offer the same new products. So we also use 0 for having such information, and 1 for not. Shipping availability is also one of important factors to affect consumers' online shopping. We used dummy variable to control this factor, coding as 1 for having free shipping and 0 for not (Table 2).

Table 2: Measures of All the Variables

Dependent Variable	Measurement
New product sales	-Log(SalesRank from Amazon.com)
Independent Variable	**Measurement**
Volume of Review	The total number of reviews
Valence of Review	The average rating of reviews
Moderating factor	**Measurement**
Stage of PLC	Dummy variable for stage of PLC: 0 for early stage; 1 for late stage. Or Ageweek of each product.
Product type	Dummy variable for product type: 0 for search product category; 1 for experience product category.
Control Variable	**Measurement**
Product subcategory	Nine dummy variables for search product; eleven dummy variables for experience product.
List price	The product price before discount
Promotion	Percentage of price reduction of list price
Other stores	Dummy variable for other stores to provide the same products: 1 for Yes; 0 for No.
Shipping availability	Dummy variable for shipping availability: 1 for Yes; 0 for No.

4.3 Pretest

4.3.1 Pretest for Product Type

In the pretest, we used 9 types of electronics, including electronics accessories, cameras, Televisions, MP3 players, computers, office electronics, GPS, equalizer and optics, and 11 types of video games, including playstations3, Xbox360, Nintendo Wii, Playstation2, Xbox, GameCube, Mac Games, Sony PSP, Nintendo DS, Game Boy Advance. First, 47 undergraduate students at a large University in Hong Kong participated in a pretest, which was conducted to identify both product stimuli for search and experience products. Second, The subjects were provided with 9 types of electronics and 11 types of video games, and were presented with five seven-point Likert items for each product, with 1=”Absolutely Disagree” and 7=”Absolutely Agree”, three items used to assess experience qualities and two items used to assess search qualities (Weathers el at. 2007). Third, responses to the items were averaged to create measures of experience and search qualities for each product, and the difference between these measures was computed (i.e., experience-search). The absolute value of the average of the differences of electronics was less than that of video games, and these average means differed significantly (electronics= -.2.176, video= 5.181; $p<0.001$). Thus, the two products can adequately represent search and experience products respectively.

4.3.2 Pretest for Reviews

Chevaliber and Mayzlin (2006) found that consumers actually read and respond to written reviews, not merely the average star rating summary statistic provided by the Web sites. Therefore, we checked the valence consistency of reviews in form of rating and text. We randomly selected 50 new search products and 50 new experience products. There are 445 reviews for search products and 478 reviews for experience products. According to Liu (2006), we selected three judges and they independently read each of the messages and assigned them to one of five categories: one star, two stars, three stars, four stars, five stars, according to the definition of Amazon rating system (Table3). From the definition, the messages classified as four stars and five stars are positive, either showing clear positive assessment of the new products or provide direct positive recommendations. The messages classified as one star and two stars are negative, either showing clear negative assessment of the new products or provide direct negative recommendations. The messages classified as three stars are neutral if they talk about the new products but not provide any positive or negative comments. The three independent codings are integrated using the majority rule: If at least two judges assign the same category, that category is used for the message. If all three judges disagree, the message is coded as disagreement. Finally, we compared the ratings assigned by the three judges with that assigned by reviewer to check the valence consistency of reviews in form of rating and text. The result is the valence of 98% of text reviews is consistent with that of ratings. Therefore, we used product ratings to measure the valence of online consumer reviews.

Table 3: Amazon Rating System

Number of stars	The meaning of stars
1 star	I hate it
2 stars	I don't like it
3 stars	It's OK
4 stars	I like it
5 stars	I love it

CHAPTER 5. RESULTS

In this chapter, the results of the hypotheses testing analyzed by using the methodology stated in Chapter 4 are reported. This chapter starts with the descriptive statistics of data collected. Next, the general steps which comprised performing hierarchical regression analysis for each hypothesis in cross-sectional analysis and panel data analysis are also described.

5.1 Descriptive Analysis

In total, we collected 417 new products for nine months, 165 search products and 252 experience products. Because some of products are not sold and some of products have missing information during the period, we exclude these kinds of products. The final sample contains 332 new products, 131 search products and 201 experience products. The rate of useful information is 79.6% for all the products, 79.4% for search products and 79.8% for experience products.

Table 4 provides some key summary statistics about the key variables in our sample. We summarized the minimum, maximum, mean and standard deviation values of all the variables. Sales ranking for experience products ranges from 131316 to 12, while sales ranking for search products ranges from 378314 to 2. The maximum volume of positive reviews (274) and negative reviews (38) for experience products is smaller than that of positive reviews (543) and negative reviews (63) for search products, and the maximum volume of positive reviews is greater than that of negative reviews in both types of products. The mean of average aggregate ratings for experience products (3.15) is greater than that for search products (1.85). Standard Deviation of volume of reviews in experience products(34.49) is greater than that in search products(32.46).

Table 4: Key Summary Statistics

Variables (experience products)	**MIN**	**MEAN**	**MAX**	**SD**
Sales Ranking (aggregate)	131316	4705.53	12	7003.11
Volume of total reviews	1	24.62	279	34.49
Volume of positive reviews	1	19.16	274	29.89
Volume of negative reviews	1	2.82	38	4.26
Percentage of positive reviews	0	14.7%	100%	21.6%
Percentage of negative reviews	0	57.2%	100%	38.6%
Average aggregate rating(rang 1-5)	1	3.15	5	1.79
Variables (search products)	**MIN**	**MEAN**	**MAX**	**SD**
Sales Ranking (aggregate)	378314	45245.4	2	64852.73
Volume of total reviews	1	12.79	641	32.46
Volume of positive reviews	1	10.44	543	27.49
Volume of negative reviews	1	1.5	63	3.54
Percentage of positive reviews	0	13.4%	100%	35%
Percentage of negative reviews	0	55.2%	100%	20.4%
Average aggregate rating(rang 1-5)	1	1.85	5	1.81

5.2 Cross-sectional Analysis

5.2.1 Data Description

We conducted a cross-sectional analysis using data in the last week of February in 2008. For the cross-sectional data, there are 319 new products including 201 new experience products and 118 new search products. Table 5 summarizes the basic information about cross-sectional data. Sales ranking for experience products ranges from 131316 to 20, while sales ranking for search products ranges from 378314 to 2. The maximum volume of positive reviews (274) and negative reviews (35) for experience products is smaller than that of positive reviews (543) and negative reviews (63) for search products, and the maximum volume of positive reviews is greater than that of negative reviews in both types of products. The mean of average aggregate ratings for experience products (3.15) is greater than that for search products (1.86). Standard Deviation of volume of reviews in experience products (46.04) is less than that in search products (60.17).

Table 5: Descriptive Statistics of Cross-Sectional Data

Variables (experience products)	**MIN**	**MEAN**	**MAX**	**SD**
Sales Ranking (aggregate)	131316	4705.53	20	12831.848
Volume of total reviews	1	24.62	279	46.04
Volume of positive reviews	1	19.16	274	40.05
Volume of negative reviews	1	2.82	35	5.18
Percentage of positive reviews	0	14.7%	100%	22.9%
Percentage of negative reviews	0	57.2%	100%	35.3%
Average aggregate rating(rang 1-5)	1	3.15	5	1.62
Variables (search products)	**MIN**	**MEAN**	**MAX**	**SD**
Sales Ranking (aggregate)	378314	45628	2	6451.25
Volume of total reviews	1	12.9	641	60.17
Volume of positive reviews	1	10.53	543	51.07
Volume of negative reviews	1	1.51	63	6.18
Percentage of positive reviews	0	33%	100%	21.8%
Percentage of negative reviews	0	7.3%	100%	32.5%
Average aggregate rating(rang 1-5)	1	1.86	5	2.08

5.2.2 Cross-sectional Analysis

We calculated the correlation coefficients for all the variables in our study to check the interrelationships between the variables. Table 6 shows the correlations between the variables. The interrelationship between the variables is less than 0.6. The cutoff of interrelationship is commonly used as 0.85. Therefore, the variables do not measure the same thing.

Table 6: Correlation Matrix for All the Variables in Cross- sectional Analysis

	SR	VA	VO	NP	PP	SH	PR	OS	PRO
Sales Ranking(SR)	1	0.655**	0.453**	0.459**	0.247**	0.474**	0.104	-0.263**	0.151**
Valence(VA)		1	0.304**	0.678**	0.338**	0.403**	0.065	-0.172**	0.060
Volume (VO)			1	0.241**	0.078	0.225**	-0.033	-0.097	0.043
Negative Percentage (NP)				1	-0.299**	0.468**	-0.291**	-0.165**	0.029
Positive Percentage (PP)					1	0.026	0.398**	-0.052	0.062
Shipping(SH)						1	-0.288**	-0.317**	0.014
Price(PR)							1	-0.024	-0.002
Other Store (OS)								1	0.009
Promotion(PRO)									1

** Correlation is significant at the 0.01 level (2-tailed).

Since we have several groups of variables as predictors, including both main effects and interactions, we adopt hierarchical regressions to test the hypotheses. First, in order to get the better result, we calculated the Z score for volume. Then, we ran a hierarchical regression analysis for hypothesis 1 regarding the effect of volume of online consumer reviews on new overall product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates and the volume of online consumer reviews. Table 7 shows that this regression model is significant (adjusted R-Square=0.672, F =69.429, P< 0.001), and coefficient of volume of online consumer reviews is positive (Standardized Beta = 0.358, P<0.001). Thus, hypothesis 1 is supported.

Table 7: Hierarchical Regression Analyses for the Effect of Volume of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.331	0.452
Adjusted R-Square	0.320	0.441
F Value	31.226	69.429
Sig.F Change	0.000	0.000
Shipping	0.402***	0.299***
Price	0.304***	0.303***
Promotion	0.137**	0.121**
Other Store(OS)	-0.091^	-0.082^
Product Type	0.183**	0.218***
Volume		0.358***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

In order to get the better result, we first calculated the Z score for valence. Then, we ran a hierarchical regression analysis for hypothesis 2 regarding the effect of valence of online consumer reviews on new overall product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates and the valence of online consumer reviews. Table 8 shows that this regression model is significant (adjusted R-Square=0.526, F =129.676, P< 0.001), and coefficient of valence of online consumer reviews is positive (Standardized Beta = 0.501, P<0.001). Thus, hypothesis 2 is supported.

Table 8: Hierarchical Regression Analyses for the Effect of Valence of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.331	0.526
Adjusted R-Square	0.320	0.517
F Value	31.226	129.676
Sig.F Change	0.000	0.000
Shipping	0.402***	0.243***
Price	0.304***	0.175***
Promotion	0.137**	0.115**
Other Store(OS)	-0.091^	-0.081*
Product Type	0.183**	0.073
Valence		0.501***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

In order to get the better result, we first calculated the Z score for valence and volume. Then, we ran a hierarchical regression analysis for hypothesis 3 regarding the effect of valence of online consumer reviews versus that of volume of online consumer reviews on new overall product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 9 shows that this regression model is significant (adjusted R-Square=0.586, F =96.866, P< 0.001). The coefficient of valence of online consumer reviews is 0.429 (P<0.001), while the coefficient of volume of online consumer reviews is 0.261 (P<0.001). The coefficient of valence of online consumer reviews is greater than that of volume of online consumer reviews. That means the effect of valence of online consumer reviews is greater than that of volume of online consumer reviews on new product sales. Thus, hypothesis 3 is supported.

Table 9: Hierarchical Regression Analyses for the Effect of Volume and Valence of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.331	0.586
Adjusted R-Square	0.320	0.577
F Value	31.226	96.866
Sig.F Change	0.000	0.000
Shipping	0.402***	0.191***
Price	0.304***	0.193***
Promotion	0.137**	0.106**
Other Store(OS)	-0.091^	-0.076^
Product Type	0.183**	0.115*
Valence		0.429***
Volume		0.261***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

According to previous studies (Basuroy et al. 2003; Eliashberg and Shugan 1997), we used the percentage of positive messages and the percentage of negative messages measure the valence of online consumer reviews. In order to get the better result, we first calculated the Z score for percentage of positive reviews and percentage of negative reviews. Then we ran a hierarchical regression analysis for hypothesis 4 regarding the effect of online negative consumer reviews versus that of online positive consumer reviews on new overall product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, percentage of online positive consumer reviews and percentage of online negative consumer reviews. Table 10 shows that this regression model is significant (adjusted R-Square=0.565, F =96.750, P< 0.001). The coefficient of percentage of online negative consumer reviews is 0.445 (P<0.001), while the coefficient of percentage of online positive consumer reviews is 0.303 (P<0.001). That means the effect of online negative consumer reviews is greater than that of online positive consumer reviews on new product sales. In another way, we calculated the rate of the number of online positive consumer reviews and the number of online negative consumer reviews for each product. That rate of the number of online positive WOM greater than the number of online negative WOM accounts for 98.1%. That means, even though online positive WOM is more than online negative WOM, the effect of online negative WOM is greater than that of online positive WOM. Thus, hypothesis 4 is supported. However, there is a problem that the coefficient of the percentage of online negative reviews is positive, which is not as we expected before. We conducted multicollinearity tests show that there is no collinearity or suppression problem, because VIF of all the variables is less than 10. The same problem also exists in the paper of Liu (2006).

Table 10: Hierarchical Regression Analyses for the Effect of Positive and Negative of Overall Data

Dependent Variable	**New Product Sales**		
Model Fitness	**Model 1**	**Model 2**	**VIF**
R-Square	0.331	0.474	
Adjusted R-Square	0.320	0.462	
F Value	31.226	42.709	
Sig.F Change	0.000	0.000	
Shipping	0.402***	0.264***	2.360
Price	0.304***	0.214***	1.455
Promotion	0.137**	0.116**	1.014
Other Store(OS)	-0.091^	-0.079^	1.133
Product Type	0.183**	0.046	3.040
Negative Percentage		0.439***	1.725
Positive Percentage		0.287***	1.409

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

In order to get the better result, we first calculated the Z score for volume and valence. Before testing hypothesis 5, we compared the differences of new product sales between new search products and new experience products. The difference emerges in our data with the effect of online WOM has greater effect on new experience product sales than on new search product sales. The differences between search products and experience products on new product sales are reported in Table 11. The role of product type was further analyzed using regression analysis and will be reported subsequently in this section.

Table 11: Role of Product Type: Differences in New Product Sales

product	Mean	SD	T-statistic	Prob>|T|
Search	-4.209	1.057	3308.54	0.0000
Experience	-2.973	0.792		

Next, we tested the hypothesis 5 regarding the effect of the volume and valence of online consumer reviews on search product sales versus experience product sales. First, we ran a hierarchical regression analysis regarding the effect of the volume and valence of online consumer reviews of all the products on new product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 9 shows that this regression model is significant (adjusted R-Square=0.586, F =96.866, P< 0.001). The coefficient of valence of online consumer reviews is 0.429 (P<0.001), while the coefficient of volume of online consumer reviews is 0.261 (P<0.001)

Second, we ran a hierarchical regression analysis regarding the effect of the volume and valence of online consumer reviews of search products and those of experience products on new product sales respectively. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product subcategory). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 12 reflects the result of regression on new product sales of search products and experience products. The predictive validity of the model as indicated by Adjusted R-Square is higher for experience products (0.599) compared to search products (0.590). The regression models are significant (P<0.001). The role of volume and valence of online consumer reviews comes out strong in both groups (For search products, Standardized Beta for volume=0.112, Standardized Beta for valence=0.391; for experience products, Standardized Beta for volume=0.401, Standardized Beta for valence=0.546). The regression coefficient is significant in both cases (P<0.001).

Table 12: Role of Product Type: Regression Analysis

Variable	Standardized Coefficient	Standard Error	T for H0: Parameter=0	Prob >|T|
Product Type = Search (Adjusted R-Square = 0.590)				
Valence	0.391	0.095	5.118	0.000
Volume	0.112	0.076	1.820	0.000
Product Type = Experience (Adjusted R-Square = 0.599)				
Valence	0.546	0.039	10.054	0.000
Volume	0.401	0.035	8.068	0.000

Then we used Chow test (Chow, 1960) to compare the regression models by product type with the general model. The Chow test is the most popular way of testing whether or not the parameter values associated with one data set are the same as those associated with another data set. The equation for the Chow test follows:

$$F=\frac{(S_C-(S_1+S_2))/(k+1)}{(S_1+S_2)/(N_1+N_2-2k-2)}. \qquad (1)$$

where k=number of parameters in the regression equation.

Here, an F –statistic is computed from the equation above. Two separate regressions allow the parameters to differ between the two populations. Sc is the sum of the squared residuals from the regression using the entire sample. S1 and S2 are the sum of squared residuals from regressions using each individual regime. N1 is the total number of observations in the sample1, and N2 is the total number of observations in the sample2. Therefore, to check whether the differences between the coefficients obtained for the different regressions reached significant levels, a Chow test was performed. The sum of square errors for each of the regressions was obtained from the analysis of variance data given in the Table 13. Chow test statistic was calculated to be 37.46. This is found to be significant at the 0.05 level. Therefore, there is statistical evidence of product type influencing the relationship between the variables in the model. Finally, we checked the coefficients of related variables in the model. The coefficient of volume of experience products (0.401) is greater than that of search products (0.112). The coefficient of valence of experience products (0.546) is greater than that of experience products (0.391). Thus, hypothesis 5a and hypothesis 5b are supported.

Table 13: The Role of Product Type: Analysis of Variance

Source	d.f.	Sum of Squares	F	Prob >|T|
General model				
Model	2	189.218	63.514	0.000
Error	317	133.637		
Product Type = Search				
Model	2	121.776	13.899	0.000
Error	115	59.576		
Product Type= Experience				
Model	2	63.606	19.267	0.000
Error	198	38.585		

In order to get the better result, we first calculated the Z score for valence and volume. Then, hierarchical regression analysis was conducted for hypothesis 6 regarding the effect of the volume of online consumer reviews on new product sales for two types of products over time. Since the PLC of new experience products is different from that of new search products, we conducted cross-sectional analysis for experience product data and for search product data separately. First, we need to determine the cutoff point of stage of PLC, and coded “week” as 0 for early stage and 1 for late stage. After trial and error, we found out the cutoff point of stage of PLC is the 14^{th} week for search products, while the cutoff point of stage of PLC is the 12^{th} week for experience products.

Then, we ran a hierarchical regression analysis for search products. Table 14 shows the results of regression analysis for the search products. In the first step, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product subcategory).In the second step, we regressed the dependent variable on all the covariates, and volume of online consumer reviews. In the third step, we regressed the dependent variables on all covariates, volume of online consumer reviews, valence of online consumer reviews and week. In the fourth step, we regressed the dependent variables on all covariates, volume of online consumer reviews, valence of online consumer reviews, week and interaction between volume and valence. In the last step, we regressed the dependent variables on all covariates, volume of online consumer reviews, week, the interaction between volume and valence and the interaction between week and volume of online consumer reviews. The high adjusted R-Square (0.679) implies that fit of the regression model is very good. The interaction between week and volume of search products (Standardized Beta= -0.119, $P<0.05$) is significant and the coefficient is negative, which means when the week is equal to 0, the coefficient of this interaction is more than the coefficient of this interaction when the week is equal to 1. In other words, the effect of the volume of online consumer reviews on new product sales in the early stage of PLC is more than that in the late stage of PLC. The result is not as what we expected. The interaction between volume and valence (Standardized Beta= -0.613, P<0.001) is significant and the coefficient is negative, which means the more positive reviews can lead to fewer new product sales and verse visa. The result is also opposite to our expectation.

In the same way, we ran hierarchical regression analysis for experience products. Table 14 shows the results of regression analysis for experience products. The high adjusted R-Square (0.623) implies that fit of the regression model is very good. The interaction between week and volume of experience products (Standardized Beta= -0.358, P<0.01) is significant and the coefficient is negative, which means when the week is equal to 0, the coefficient of this interaction is more than the coefficient of this interaction when the week is equal to 1. In other words, the effect of the volume of online consumer reviews on new product sales in the early stage of PLC is more than that in the late stage of PLC. The result is not as what we expected. The interaction between volume and valence (Standardized Beta= -0.551, P<0.05) is significant and the coefficient is negative, which means the more positive reviews can lead to fewer new product sales and verse visa. The result is also opposite to our expectation.

Because the results are contradicted to our expectation, we conducted the multicollinearity test before we made a conclusion for this hypothesis. The results in Table 14 and Table 15 show that there is serious multicollinearity among several terms (VIF >10). Therefore, we used standardized scores to correct the multicollinearity problem. After running ridge regression, all the variables of VIF are smaller than 10 and most of them range from 1 to 2, which indicate that the correction procedure is effect. Since we used one-week data to analyze our hypothesis, meaning our sample size is not very large, we reported the results with significant level lower than 0.1 (Luo, 1998).

Table 17 shows the results of ridge regression analysis for search products. The high adjusted R-Square (0.537) implies that fit of the regression model is very good. The interaction between week and volume of search products (Standardized Beta=0.190, P<0.001) is significant and the coefficient is positive, which means when the week is equal to 0, the coefficient of this interaction is less than the coefficient of this interaction when the week is equal to 1. In other words, the effect of the volume of online consumer reviews on new product sales in the early stage of PLC is less than that in the late stage of PLC. The interaction between volume and valence is significant(P<0.05) and positive for search products(0.057), which means the more positive reviews can lead to greater effect on new product sales, and the fewer positive reviews can lead to less effect on new product sales; and verse visa. Table 16 shows the results of ridge regression analysis for experience products. The high adjusted R-Square (0.643) implies that fit of the regression model is very good. The interaction between volume and valence is significant(P<0.05) and positive for experience products(0.132), which means the more positive reviews can lead to greater effect on new product sales, and the fewer positive reviews can lead to less effect on new product sales; and verse visa. The interaction between week and volume of search products (Standardized Beta=0.141, P<0.05) is significant and the coefficient is positive, which means when the week is equal to 0, the coefficient of this interaction is less than the coefficient of this interaction when the week is equal to 1. In other words, the effect of the volume of online consumer reviews on new product sales in the early stage of PLC is less than that in the late stage of PLC. Thus, H6 is supported.

Table 14: Hierarchical Regression Analyses for the Effect of Volume of Search Products

Dependent Variable	New Product Sales					
Model Fitness	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**VIF**
R-Square	0.569	0.671	0.722	0.722	0.729	
Adjusted R-Square	0.515	0.623	0.678	0.675	0.679	
F Value	9.099	4.256	20.984	0.032	19.012	
Sig.F Change	0.000	0.000	0.000	0.874	0.000	
Shipping	0.515***	0.274***	0.252***	0.255***	0.229**	1.881
Price	0.275***	0.164*	0.157*	0.157*	0.155*	1.391
Promotion	0.208**	0.182**	0.159**	0.158**	0.152**	1.368
Other Store(OS)	-0.113	-0.192	-0.115^	-0.115^	-0.118^	6.877
SubC1	-0.213	-0.198	0.159	-0.214	-0.210	1.155
SubC2	-0.081	-0.078	-0.215	-0.168	-0.162	9.142
SubC3	-0.124	-0.188	-0.169	-0.257	-0.250	10.265
SubC4	-0.138	-0.147	-0.257	-0.191	-0.195^	4.848
SubC5	-0.099	-0.134	-0.191	-0.202	-0.222	19.781
SubC6	-0.037	-0.049	-0.204	-0.138	-0.143	20.942
SubC7	-0.076	-0.054	-0.138	-0.049	-0.044	2.992
SubC8	-0.106	-0.150	-0.049*	-0.188*	-0.186*	2.699
SubC9	-0.101	-0.138	-0.188^	-0.142	-0.137	2.664
Volume		0.112^	-0.142	-0.067	-0.546	340.690
Valence		0.391***	0.079***	0.391*	0.435*	11.415
Week			0.366***	-0.247***	-0.209**	1.506
Interaction between volume and valence				0.142	-0.613***	320.656
Interaction between week and volume					-0.119*	2.260

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

Table 15: Hierarchical Regression Analyses for the Effect of Volume of Experience Products

Dependent Variable			**New Product Sales**			
Model Fitness	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**VIF**
R-Square	0.165	0.622	0.630	0.643	0.658	
Adjusted R-Square	0.104	0.590	0.596	0.608	0.623	
F Value	2.674	113.192	3.603	6.762	8.232	
Sig.F Change	0.001	0.000	0.059	0.010	0.005	
Shipping	0.052	0.085^	0.096^	0.091^	0.090^	1.291
Price	0.251***	0.087	0.085	-0.058	-0.075	1.510
Promotion	0.117^	0.032	0.029	0.018	0.004	1.389
Other Store(OS)	-0.082	-0.070	-0.065	-0.062	-0062	1.097
SubC1	-0.143^	-0.090^	-0.107*	-0.116*	-0.125*	1.406
SubC2	-0.194*	-0.065	-0.087	-0.098^	-0.115*	1.704
SubC3	-0.0560	0.016	0.009	0.012	-0.010	1.498
SubC4	-0.091	-0.010	-0.007	0.011	-0.003	1.141
SubC5	0.008	0.019	0.001	0.006	0.003	1.071
SubC6	-0.088	-0.070	-0.073	-0.075	-0.079^	1.163
SubC7	-0.177*	-0.027	-0.035	-0.021	-0.054	1.673
SubC8	-0.019	0.057	0.057	0.051	0.052	1.046
SubC9	-0.304***	-0.224***	-0.224***	-0.190***	-0.194***	1.483
SubC11	-0.091	-0.022	-0.022	-0.026	-0.026	1.043
Volume		0.574***	0.588***	0.205***	0.461***	34.872
Valence		0.359***	0.348***	0.335***	0.113	4.514
Week			-0.091^	-0.126*	-0.131**	1.262
Interaction between volume and valence				-0.633**	-0.551*	31.083
Interaction between week and volume					-0.358**	8.376

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

Table 16: Ridge Regression Analyses for the Effect of Volume of Search Products

Dependent Variable	**New Product Sales**
Model Fitness	
R-Square	0.582
Adjusted R-Square	0.537
F Value	12.749
Sig.F Change	0.000
Shipping	0.043^
Price	0.013^
Promotion	0.039*
Other Store(OS)	-0.049*
SubC1	-0.029
SubC2	-0.018
SubC3	0.053*
SubC4	0.006
SubC5	0.012
SubC6	-0.039
SubC7	0.01
SubC8	-0.036*
SubC9	-0.129**
Volume	0.261***
Valence	0.255***
Week	-0.045
Interaction between volume and valence	0.057*
Interaction between week and volume	0.190***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

Table 17: Ridge Regression Analyses for the Effect of Volume of Experience Products

Dependent Variable	New Product Sales
Model Fitness	
R-Square	0.698
Adjusted R-Square	0.643
F Value	12.706
Sig.F Change	0.000
Shipping	0.1789*
Price	0.131*
Promotion	0.115^
Other Store(OS)	-0.073
SubC1	-0.059
SubC2	-0.016
SubC3	-0.041
SubC4	-0.061
SubC5	-0.001
SubC6	0.098
SubC7	-0.003
SubC8	-0.076
SubC9	-0.049
SubC10	0.067
SubC11	-0.017
Volume	0.153*
Valence	0.232**
Week	-0.069
Interaction between volume and valence	0.132*
Interaction between week and volume	0.141*

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

5.3 Panel Data Analysis

We conducted cross-sectional analysis to test our hypotheses, but it may have cohort bias effect. We conducted panel data analysis for all the hypotheses. We conducted hierarchical regression to test the first five hypotheses, and used fixed effect model to test the last hypothesis, using STATA. Some of the hypotheses are also supported by the results as mentioned above, while some are not. More specifically, the first five hypotheses are supported, the results as same as those of cross-sectional analysis. The last hypothesis is not supported, and the result is contrary to that of cross-sectional analysis. Overall, panel data analyses show that the results are in fact more complicated. Figure 17 and Figure 18 shows the dynamic pattern of sales for selected new search products and new experience products respectively.

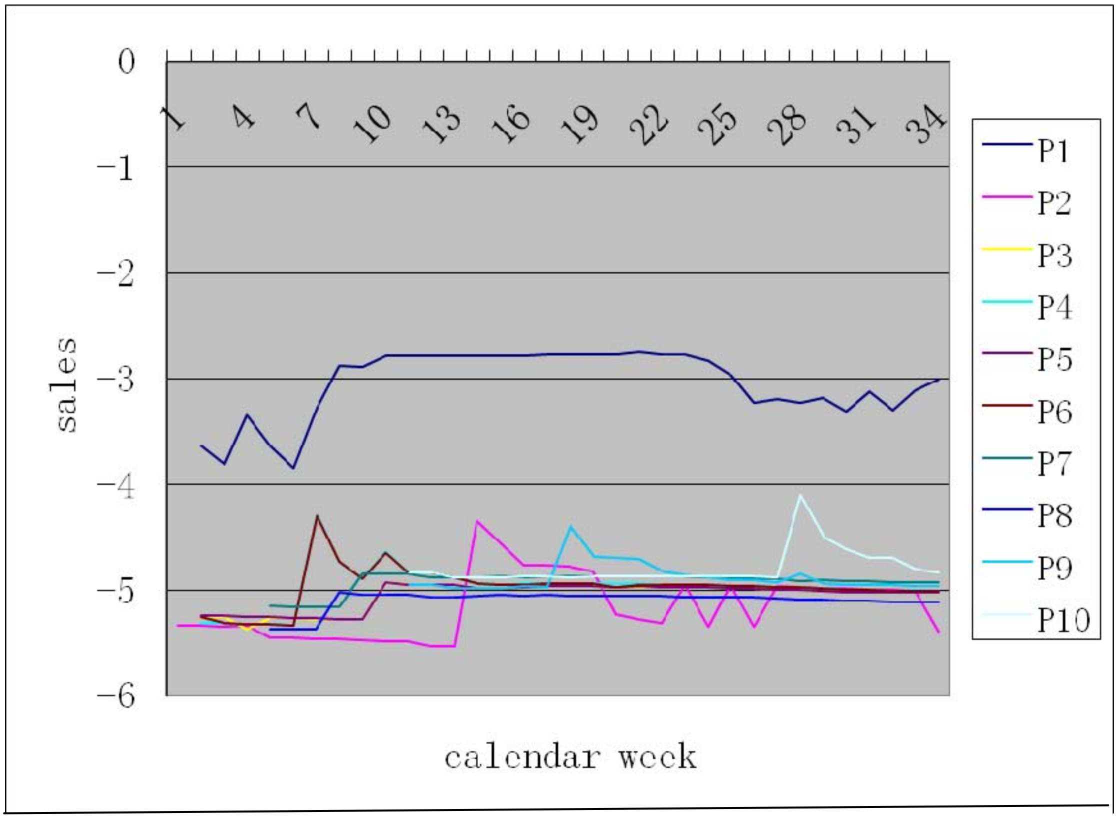


Figure 17: Graphics for New Search Product Sales Over Time

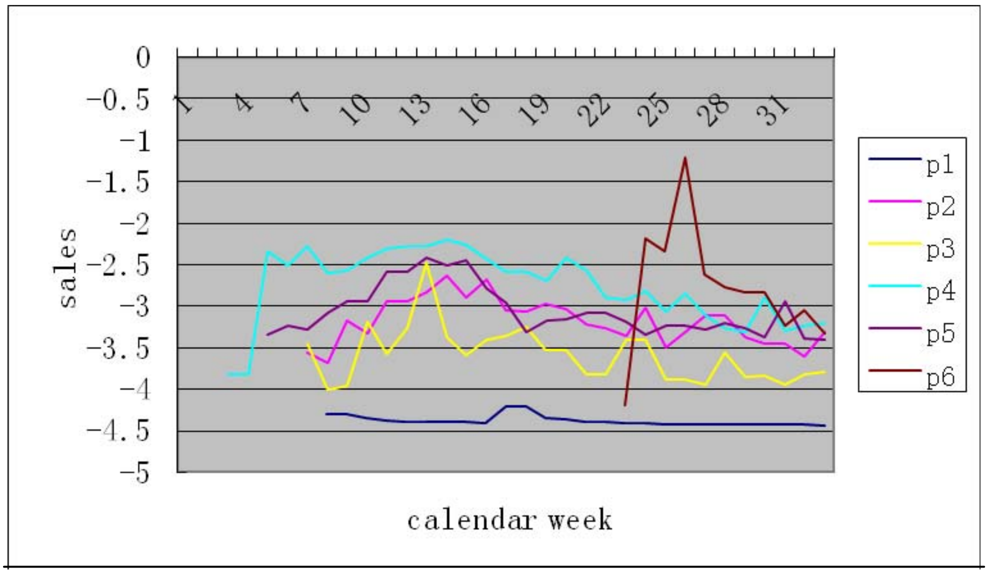


Figure 18: Graphics for New Expeience Product Sales Over Tim

Then, we calculated the correlation coefficients for all the variables in our study to check the interrelationships between the variables. Table 17 shows the correlations between the variables. The interrelationship between the variables is less than 0.6. The cutoff of interrelationship is commonly used as 0.85. Therefore, the variables do not measure the same thing.

Table 18: Correlation Matrix for All the Variables in Panel Data Analysis

	SR	**VO**	**VA**	**NP**	**PP**	**SH**	**PR**	**OS**	**PRO**
Sales Ranking(SR)	1	0.254**	0.605**	0.078**	0.593**	0.566**	0.277**	-0.208**	0.630**
Volume(VO)		1	0.234**	0.051**	0.239**	0.275**	-0.006	-0.065**	0.228**
Valence(VA)			1	0.187**	0.942**	0.508**	0.397**	-0.193**	0.557**
Negative Percentage (NP)				1	0.038*	0.086**	-0.079**	0.003	0.139**
Positive Percentage (PP)					1	0.511**	0.456**	-0.206**	0.572**
Shipping(SH)						1	0.023	-0.155**	0.535**
Price(PR)							1	-0.220**	0.263**
Other Store (OS)								1	-0.185**
Promotion(PRO)									1

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

We ran hierarchical regression to test the first five hypotheses. To test hypothesis 1 regarding the effect of volume of online consumer reviews on new product sales, at step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates and the volume of online consumer reviews. Table19 shows that this regression model is significant (adjusted R-Square=0.511, F =1301.81, P< 0.001), and coefficient of volume of online consumer reviews is positive (Standardized Beta = 0.279, P<0.001). Thus, hypothesis 1 is supported.

Table 19: Hierarchical Regression Analyses for the Effect of Volume of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.439	0.511
Adjusted R-Square	0.438	0.511
F Value	1166.02	1301.81
Sig.F	0.000	0.000
Shipping	0.325***	0.273***
Price	0.146***	0.149***
Promotion	0.197***	0.163***
Other Store(OS)	-0.047***	-0.039***
Product Type	0.319***	0.318***
Volume		0.279***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

To test hypothesis 2 regarding the effect of valence of online consumer reviews on new product sales, at step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates and the valence of online consumer reviews. Table 20 shows that this regression model is significant (adjusted R-Square=0.561, F =15966.80, P< 0.001), and coefficient of valence of online consumer reviews is positive (Standardized Beta = 0.427, P<0.001). Thus, hypothesis

2 is supported.

Table 20: Hierarchical Regression Analyses for the Effect of Valence of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.439	0.562
Adjusted R-Square	0.438	0.561
F Value	1166.02	1596.80
Sig.F	0.000	0.000
Shipping	0.325***	0.253***
Price	0.146***	0.056***
Promotion	0.197***	0.103***
Other Store(OS)	-0.047***	-0.045***
Product Type	0.319***	0.158***
Valence		0.427***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

To test hypothesis 3 regarding the effect of valence of online consumer reviews versus that of volume of online consumer reviews on new product sales, at step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 21 shows that this regression model is significant (adjusted R-Square=0.596, F =1576.83, P< 0.001). The coefficient of valence of online consumer reviews is 0.367 (P<0.001), while the coefficient of volume of online consumer reviews is 0.199 (P<0.001). That means the effect of valence of online consumer reviews is greater than that of volume of online consumer reviews on new product sales. Thus, hypothesis 3 is supported.

Table 21: Hierarchical Regression Analyses for the Effect of Volume and Valence of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.439	0.597
Adjusted R-Square	0.438	0.596
F Value	1166.02	1576.83
Sig.F Change	0.000	0.000
Shipping	0.325***	0.226***
Price	0.146***	0.071***
Promotion	0.197***	0.092***
Other Store(OS)	-0.047***	-0.039***
Product Type	0.319***	0.179***
Valence		0.367***
Volume		0.199***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

To test hypothesis 4 regarding the effect of online negative consumer reviews versus that of online positive consumer reviews on new product sales, at step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, percentage of online positive consumer reviews and percentage of online negative consumer reviews. Table 22 shows that this regression model is significant (adjusted R-Square=0.525, F =1179.06, P< 0.001). The coefficient of percentage of online negative consumer reviews is 0.347 (P<0.001), while the coefficient of percentage of online positive consumer reviews is 0.158 (P<0.001). That means the effect of online negative consumer reviews is greater than that of online positive consumer reviews on new product sales. Thus, hypothesis 4 is supported. However, there is the same problem with the result by cross-sectional analysis. The coefficient of online negative reviews is positive rather than negative.

Table 22: Hierarchical Regression Analyses for the Effect of Positive and Negative of Overall Data

Dependent Variable	**New Product Sales**	
Model Fitness	**Model 1**	**Model 2**
R-Square	0.439	0.525
Adjusted R-Square	0.438	0.525
F Value	1166.02	1179.06
Sig.F Change	0.000	0.000
Shipping	0.325***	0.291***
Price	0.146***	0.102***
Promotion	0.197***	0.122***
Other Store(OS)	-0.047***	-0.054***
Product Type	0.319***	0.151***
Negative Percentage		0.347***
Positive Percentage		0.158***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

To test hypothesis 5, first, we ran hierarchical regression regarding the effect of the volume and valence of online consumer reviews of all the products on new product sales. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product type). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 21 shows that this regression model is significant (adjusted R-Square=0.596, F =1576.83, P< 0.001). The coefficient of valence of online consumer reviews is 0.367 (P<0.001), while the coefficient of volume of online consumer reviews is 0.199 (P<0.001).

Second, we ran a hierarchical regression analysis for hypothesis 5 regarding the effect of the volume and valence of online consumer reviews of search products and those of experience products on new product sales respectively. At step one, we regressed the dependent variable on all covariates (shipping, price, promotion, other stores and product subcategory). At step two, we regressed the dependent variable on all the covariates, the valence of online consumer reviews and volume of online consumer reviews. Table 23 shows the predictive validity of the model as indicated by R-Square change is higher for experience products (0.307) compared to search products (0.045). The regression models are significant (P<0.001). The role of volume and valence of online consumer reviews comes out strong in both groups (Table 23).

Then we used Chow test to compare the regression models by product type with the general model (Table 24). Chow test statistic was calculated to be 316.81. This is found to be significant at the 0.05 level. Therefore, there is statistical evidence of product type influencing the relationship between the variables in the model. Finally, we checked the coefficients of related variables in the model. The coefficient of volume of experience products (0.376) is greater than that of search products (0.147). The coefficient of valence of experience products (0.379) is greater than that of experience products (0.282). Thus, hypothesis 5a and hypothesis 5b are both supported.

Table 23: Role of Product Type: Regression Analysis

Variable	Standardized Coefficient	Standard Error	T for H0: Parameter=0	Prob >|T|
Product Type = Search (Adjusted R-Square = 0.045)				
Valence	0.282	0.013	12.55	0.000
Volume	0.147	0.0003	4.94	0.000
Product Type = Experience (Adjusted R-Square = 0.307)				
Valence	0.379	0.006	27.71	0.000
Volume	0.376	0.0003	29.51	0.000

Table 24: Role of Product Type: Analysis of Variance

Source	d.f.	Sum of Squares	R-Square Change	Prob >|T|
General model				
Model	2	5231.951	0.596	0.000
Error	7467	3537.011		
Product Type = Search				
Model	2	1809.629	0.045	0.000
Error	2845	1370.177		
Product Type= Experience				
Model	2	356.704	0.307	0.000
Error	4619	2541.806		

Hierarchical regression analysis was then conducted for hypothesis 6 regarding the effect of the volume of online consumer reviews on new product sales for two types of products over time. Since the PLC of new experience products is different from that of new search products, we used fixed effect model to analyze experience product data and search product data respectively.

Then, we ran a hierarchical regression analysis for search products. Table 25 shows the results of regression analysis for the search products. The high R-Square (0.104) implies that fit of the regression model is good. The interaction between ageweek and volume of search products (Standardized Beta= -0.002, P<0.001) is significant and the coefficient is negative, which means the effect of online WOM decreases with time. In other words, the effect of the volume of online consumer reviews on new product sales in the early stage of PLC is greater than that in the late stage of PLC. It is not as we expected. The interaction between volume and valence is negative (-0.0002), which means the more positive online WOM can lead to fewer product sales. It is contradictory to our expectation.

In the same way, we ran hierarchical regression analysis for experience products. Table 26 shows the results of regression analysis for experience products. The R-Square (0.163) implies that fit of the regression model is good. The interaction between ageweek and volume of experience products (Standardized Beta=0.00003, P<0.001) is significant and the coefficient is positive, which means the effect of online WOM on new product sales increases with time. In other words, the effect of the volume of online consumer reviews on new product sales in the late stage of PLC is greater than that in the early stage of PLC. It is as we expected. The interaction between volume and valence is positive (0.004), which means more positive online

WOM can lead to more product sales. However, the coefficient of volume is negative (-0.023). It contradicted the results of previous hypotheses. Thus, H6 is not supported.

Table 25: Fixed Effect Model for the Effect of Volume of Search Products

Dependent Variable	**New Product Sales**
Model Fitness	
R-Square	0.104
F Value	24.1
Sig.F	0.000
Shipping	-0.764
Price	0.001
Promotion	0.347***
Other Store(OS)	-0.303
SubC1	(dropped)
SubC2	-0.096
SubC3	-0.102
SubC4	(dropped)
SubC5	(dropped)
SubC6	-0.289
SubC7	-0.273
SubC8	(dropped)
SubC9	(dropped)
Volume	0.043***
Valence	0.044***
AgeWeek	0.006***
Interaction between volume and valence	-0.009***
Interaction between ageweek and volume	-0.002***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

Table 26: Fixed Effect Model for the Effect of Volume of Experience Products

Dependent Variable	**New Product Sales**
Model Fitness	
R-Square	0.163
F Value	129.7
Sig.F	0.000
Shipping	0.048^
Price	0.006*
Promotion	0.052**
Other Store(OS)	(dropped)
SubC1	0.538
SubC2	0.728^
SubC3	-0.185
SubC4	0.270
SubC5	(dropped)
SubC6	(dropped)
SubC7	0.127
SubC8	(dropped)
SubC9	-0.047
SubC10	(dropped)
SubC11	(dropped)
Volume	-0.023***
Valence	0.0175***
AgeWeek	-0.013***
Interaction between volume and valence	0.004***
Interaction between ageweek and volume	0.00003***

Note: *: Sig.<=0.05, **: Sig.<=0.01, ***: Sig.<=0.001,^.Sig.<=0.1

5.4 Summary

To conclude this chapter, the findings confirm the six connections among volume of consumer reviews, valence of consumer reviews, product type, and stage of PLC in the proposed conceptual model by using hierarchical regression technique and fixed effect model. Table 27 summarizes the results of the hypothesis testing in cross-sectional analysis and panel data analysis. All of the hypotheses are statistically supported by cross-sectional data, but not all supported by time series data.

Table 27: Summary of Hypotheses Results

Hypotheses	Cross-sectional Analysis	Panel Data Analysis
H1: The more the volume of online consumer reviews, the greater impact it has on the new product sales.	Supported	Supported
H2: The more positive the valence of online consumer reviews, the greater impact it has on new product sales.	Supported	Supported
H3: Valence of online consumer reviews has greater impact on new product sales than volume of online consumer reviews.	Supported	Supported
H4: Online negative consumer reviews have greater impact on new product sales than online positive consumer reviews.	Supported	Supported
H5a: The volume of online consumer reviews has greater impact on new experience product sales than new search product sales.	Supported	Supported
H5b: The valence of online consumer reviews has greater impact on new experience product sales than new search product sales.	Supported	Supported
H6: The effect of volume of online consumer reviews on the new product sales is greater in the late stage of PLC than in the early stage of PLC.	Supported	Not supported

CHAPTER 6. DISCUSSION

The last chapter proceeds as follows. First, the findings of this study to WOM marketing are discussed. Second, both theoretical implications and managerial implications are provided. Finally, the limitations of this study are pointed out with possible directions for future research.

6.1 Findings

This study has made an initial attempt to explore the role of product type in the impact of online WOM on new product sales on Amzon.com. This study has several important findings. First, the findings suggest that online consumer WOM affects consumers' purchasing behavior at Amazon.com. Specifically, two measures of online consumer WOM have positive impact on new product sales. That is, the higher volume, the greater its impact on new products sales. The more positive the valence of online consumer reviews, the greater positive impact it has on new product sales. In addition, online positive WOM is positively related with new product sales, but online negative WOM is not necessary to relate with new product sales negatively. Negative WOM is also positive to new product sales. Therefore, volume and valence are two good measures of online WOM to test the relationship between online WOM and new product sales.

Second, two measures of online consumer WOM have different effect on new product sales. The effect of valence of online consumer reviews on new product sales is greater than that of volume of online consumer reviews. This finding solves the inconsistency about which measure of online WOM affects new product sales in the previous studies (Liu 2006; Duan et al 2005; Chevalier and Mayzlin 2006).

Third, we investigated the role of product type in the relationship between online WOM and new product sales. Product type moderates the relationship between volume of online consumer WOM and new product sales. Also, it moderates the relationship between valence of online consumer WOM and new product sales. More specifically, the volume of online consumer WOM influences new experience product sales more than new search product sales. Similarly, the valence of online consumer WOM influences new experience product sales more than new search product sales. We can see the online WOM has different impact on the sales of different types of new products.

Fourth, online negative consumer WOM influences online new product sales more than online positive consumer WOM. This finding reflects that consumers pay more attention to online negative WOM more than online positive WOM, though there are more positive online WOM than negative WOM. However, although the magnitude of online negative WOM is greater than that of online positive WOM, the sign of online negative WOM is positive, which is counter-intuitive. This problem also exists in other paper (Liu 2006). That means negative reviews do not necessarily have a negative effect. On the contrary, they may help with promoting the products. This is totally contrary to the conventional wisdom - bad news travel faster and hurt worse. In our case, bad news can be good. We offer one theoretical explanation called the inoculation theory (McGuire 1961). This theory is used to explain more about how attitudes and beliefs change, and more importantly, how to keep original attitudes and beliefs consistent in the face of persuasion attempts. It has been assessed in varied context, including politics, health campaigns, and marketing among others. In our context, this theory is applied to explain the phenomenon that once bad reviews have been posted, people are no longer so negative about the product.

Finally, the hypothesis that the effect of volume of online consumer reviews is greater in the late stage of PLC than in the early stage of PLC is supported by cross-sectional analysis, but is not supported by panel data analysis. The inconsistent results from panel data analysis could be due to some reasons. Because we used sales ranking to replace real sales as dependent variable, but sales' ranking, unlike actual sales data, is not cumulative. According to Amazon.com, sales ranking is the ranking of products based on weekly sales adjusted by cumulative sales. It can be a problem to use sales ranking as dependent variable to test the last hypothesis by panel data analysis. Therefore, we cannot give a definitive answer to this problem at this point.

6.2 Implications of This Study

This research has both the theoretical implications and managerial implications of the impact of online WOM on new product sales.

6.2.1 Theoretical Implications

Several theoretical implications can be derived from the findings of current study for academics. First, Innovation Adoption Theory can be applied to online environment, because the role of online WOM on new product sales was tested by applying Innovation Adoption Theory online successfully. In the previous studies, the scholars usually use this theory in offline setting. This study enlarges the range of application of this theory. Furthermore, WOM can be operationalized, which is breakthrough in the WOM marketing field. Before, the traditional techniques do not measure WOM directly. Using online consumer reviews is a new way to collect WOM information to test Bass Model. It is easier and cheaper for researchers to collect such information than before.

Second, two measures of online WOM can be used to test the relationship between online WOM and new product sales. Volume and valence are good indicators to test such relationship. It is consistent with the result of previous related studies (Chatterjee 2001; Dellarocas et al 2004; Godes and Mayzline 2004)

Third, the valence of online WOM influences new product sales more than the volume of online WOM does. In the previous studies, some scholars think the volume of WOM influences product sales, rather than the valence of WOM. Others have the opposite opinion about it. The study solves this inconsistency.

Fourth, product type has a moderating effect on the relationship between online WOM and new product sales. That is, the effect of online WOM has greater impact on new experience product sales than on new search product sales. Therefore, this good moderator can be used in other research area, such as new product diffusion. Other researchers can incorporate product type in the Bass Model to test it in the future study.

Finally, the finding that the effect of online WOM is greater in the late stage of PLC than in the early stage of PLC is inconclusive, because we have different results in the cross-sectional analysis and panel data analysis for this hypothesis. If researchers are interested in this issue, they can use other data to test this hypothesis in the future studies.

6.2.2 Managerial Implications

The findings of this study also indicate several possible interesting practical directions for current practitioners. First, the findings highlight the need for practitioners to observe and respond to online WOM communication actively.

According to online consumer reviews, practitioners can develop more suitable marketing strategy and promote consumer advocacy to create positive reviews when they launch new products.

Second, manufactures may also incorporate valuable consumer feedback in the development of new products, especially for the negative WOM. It is better for practitioners to collect negative opinions from consumers to improve the quality of products in these aspects, and retain the good quality of products so that practitioners can gain more market shares and keep their competitive advantage. However, it is not necessary for practitioners to manipulate the negative reviews posted by others on the website, because according to our finding, online negative reviews may not hurt new product sales too much, and may improve the sales instead.

Third, because online WOM affects new experience product sales more than new search product sales, the extent to which practitioners in different industries pay attention to online consumer WOM may be different. For examples, practitioners in IT industries may pay attention to online consumer WOM less than those in entertainment industries do, because the online WOM influences the sales of new products in IT industries less than those in entertainment industries do.

Fourth, online WOM is very useful for consumers to evaluate the quality of experience products. Usually, search products are sold well in the online environment, but the experience products are not, since search products have more tangible attributes and lower perceived risk than experience products (Erdem and Swait 1998). Therefore, the third party information, such as online WOM, provides more vivid information for experience products, decreases the perceived risk of them, makes consumers willing to buy such products online and gives e-retailers more opportunities to sell different kinds of products, which they did not sell before, because of high-perceived risks consumers confronted with.

Last, although our finding in cross-sectional analysis about the role of stage of PLC in new product sales is not consistent with that in panel data analysis, yet it is better for practitioners to pay attention to the effect of online WOM after introduction stage of PLC, because, at least, the effect of online WOM on new product sales is more influential than ever before.

6.3 Limitations and Suggestions

Although this study produces interesting and meaningful findings, the study has its limitations. First, we collected data from only one online retailer, which is Amazon.com, so there may be sample selection bias. Although the data from Amazon.com are reliable, and more researchers use the data from this website, the results may be better if they can be compared with data from other sources. Second, we collected data for 9 month, which may be short. Maybe it cannot reflect the whole process of PLC. Therefore, future research should collect for a longer time.

Moreover, there are no control variables for offline competition and offline promotion of each new product, such as competitive price from offline stores. It is better to add more control variables in the future studies. In addition, we do not yet control for brand image of the product. While we try to control for some effects of brand through price and the product category dummy variables, we do not explicitly control for brand. The individual coding of brand for each individual product is a long process, since there are many brands in search products and experience products. However, we hope to control for brand in future study, as it is an important factor (Amblee and Bui 2007).

Fifth, for our data, there are many subcategories in each product type, so product heterogeneity may influence the results. Different products have different characteristics. If such difference is too high, the result is not reliable to use such kind of data to test our hypotheses. Therefore, we will choose a narrower product category in the future study.

Sixth, we used the average rating to measure the valence of online WOM, rather than percentage of online positive reviews and percentage of online negative reviews. This method maybe loses some information. For example, two products may have same average rating but with distinct percentage of negative reviews (say 20% versus 40%). Therefore, the average rating may not reflect the actual structure of online reviews, and further influence the results of our study.

Finally, we used sales ranking of new products, rather than real sales data, so it is a problem for us to test the last hypothesis using noncumulative data. Because it is difficult for us to collect actual sales data from Amazon.com, several researchers have attempted to change our sales ranking into time series data by using the method of Reverse Engineering. Sornette et al. (2004) transformed book sales ranking into time series sales data by purchasing books from Amazon.com and record the changes in sales ranking. The specific steps are described as follows.

Every book that has sold at least one copy on the online retailer Amazon is automatically assigned a sales rank. Typically, two (respectively ten) sales a day puts a title in the top 10,000 (respectively 1,000) sellers. The top 100 (respectively 10) sell more than about 30 (respectively 100) books per day through Amazon. Amazon.com updates the ranks of its top 10,000 books every hour, according to a formula accounting for recent sales and the entire sales history of the book. Direct sales are confidential data but their statistical properties can be reconstructed approximately by careful observations. The complementary cumulative distribution P(s) of sales s can be approximated by a stationary power law $P(s) = C/s\mu$ with $\mu \approx 2$ in the range of sales from a few books sold per day to a few hundred. They use this power law to transform book ranks $r(s) = NP(s)$ into sales s according to the formula $s = (NC/r)1/\mu$, where N is the total number of Books used to normalize the distribution. Thus, a time series of the rank r of a given book as a function of time, sampled at a given rate, can be transformed into a time series of instantaneous sales flux, through this conversion.

However, their research focuses on the sales rank of books sold at Amazon.com. It is unclear whether the same process can be used to "reverse engineer" the sales rank data of other products, such as video games and consumer electronics, into proxy sales volume. If such transformed data from sales rank is feasible and proven valid in the future, panel data analysis can help assessing the effect of online consumer reviews on the sales of new products.

Appendix A: Pretest Questionnaire

Hello, I'm an M.Phil candidate of Marketing and International Business Department in Lingnan University. I'm now conducting a questionnaire survey for my final dissertation. Please carefully read the instructions followed and kindly help me complete this questionnaire.

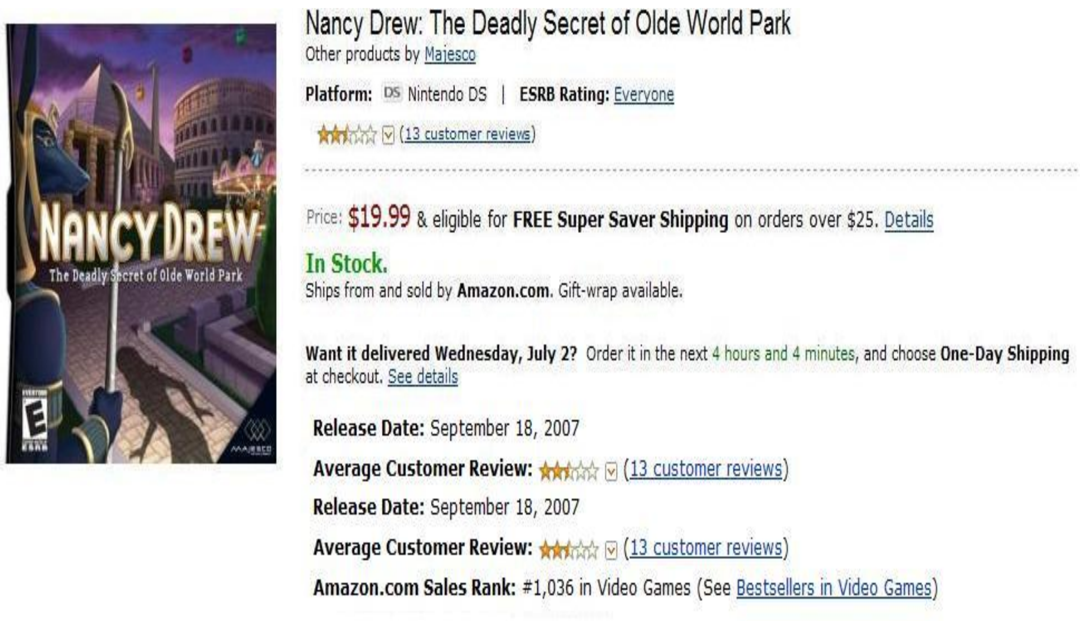
How much do you agree with the following statements? Please respond to the following statements on the scales of 1-7 regarding **video games and electronics.**

Please note:	1= Absolutely Disagree	2= Strongly Disagree	3= Somewhat Disagree	4= Neutral	5= Somewhat Agree	6= Strongly Agree	7= Absolutely Agree

1. It's important for me to see this product to evaluate how well it will perform.	1	2	3	4	5	6	7
2. It's important for me to touch this product to evaluate how well it will perform.	1	2	3	4	5	6	7
3. It's important for me to hear this product to evaluate how well it will perform.	1	2	3	4	5	6	7
1. I can adequately evaluate this product using only information provided by the retailer or manufacturer about the product's attributes and features.	1	2	3	4	5	6	7
2. I can evaluate the quality of this product simply by reading information about the product.	1	2	3	4	5	6	7

----- Thank you for your kind help. -----

Appendix B: Example of a Video Game on Amazon.com



#1 Text review

I have played every Nancy Drew PC game and have enjoyed them all (some more than others). I was looking forward to this release from the time I heard about it and even pre-ordered a copy before it came out to make sure I got one. It really is like simply following a story. When you walk into an area, everything you need to check out already has magnifying glasses on it. All exits are already marked with symbols. To "solve" things, like getting a character to talk or opening a locked door, you just have to play some very simplistic mini-games. Everything was much too easy and the game can be finished in just one day. It would have been a much better game if they had made it a little harder. You should have to look around to find the things you need in a room. You should have choices of where to go, not automatically be sent to the next thing you need to do. Maybe it would be a good choice for a young child, but if you enjoyed the Nancy Drew PC games and are expecting something similar, don't waste your money. Or at least wait to find a used copy because they should be available in stores within another day or two.

According to the definition of Amazon Rating System, Please rate this text review.

Appendix C: Example of a Electronics on Amazon.com

Apple iPod nano 8 GB Pink (3rd Generation)
Other products by Apple
(795 customer reviews) | More about this product

Size Name: 8 GB
First Select Size Name

Color Name: Pink
Then Select Color Name

List Price: ~~$199.00~~
Price: $185.95 & this item ships for **FREE with Super Saver Shipping**. Details
You Save: $13.05 (7%)
Special Offers Available

Date first available at Amazon.com: January 22, 2008

Average Customer Review: (795 customer reviews)

Amazon.com Sales Rank: #95 in Electronics (See Bestsellers in Electronics)

#1 Text review

If 'TV out' isn't important to you, or you don't care about playing podcasts back to back without fiddling with the ipod, then I'm sure you'll still love the new 3g nano. I like the video feature, the size (great for commuting), style, and colors of the new nano 3g, and iPods have the easiest/best way of selecting and sorting through music of any MP3 player out there. (I've tried a couple other brands.) But....

...in my case, one of the key reasons I bought the 3g was so that I could display photos or video on a TV. Unfortunately, that feature requires the purchase of a new cable which costs 50 bucks(the old AV cables don't work. The new cables connect through the docking port, not through the headphone input.) Of course this is something most people won't find out till they buy the product and the old AV cable. Not only do you need a new cable, but I went to many stores to get the new cable and none of them had it in stock. I finally had to order it directly from the iTunes store. I suppose someday soon, 3rd party cables will be made for one third the cost of the new AV cable made by Apple, but if you want the video out feature now, be prepared to fork over another 50 bucks. Yuck!

Also disappointing to me was a change to the software that significantly impacts what I use the ipod for. I mostly listen to podcasts and like to download all my favorites and then listen to them all without messing with the ipod (very nice feature when you're working out for an hour or more and don't want to have to mess with the ipod on the go). On the old ipod, I could find my podcasts on the music menu under "genres" and could click on "podcasts" and "all" and it would play all of them without my ever having to touch it again. Cool!!! The new ipod doesn't allow this. Not cool!! Podcasts have been moved to the root menu so they no longer show up on the music menu and there is no way to play them all non-stop. (If anyone finds a way to do this, please make a comment.) So, now when I'm on a long ride on my bike, or I'm in traffic, I have to stop and fumble with the 3g after the end of each podcast. That is really annoying and what used to be a great feature of the 2g nano, suddenly becomes impossible on the 3g. Bummer! Now, I'm back to using my 2g nano on my biking commute.

Update (Jan 12)... The 'shuffle on' setting is what has caused my podcasts to stop playing back to back. If shuffle is set to 'off' they play without touching the iPod. Thanks for the comments that led to this discovery. Still, there hasn't been a software fix for this and it is annoying to have to fiddle with the shuffle setting depending on whether I want to listen to music or podcasts. Hello Apple!

Finally, the 3g nano has some compatibility problems with other products. For example, I bought the iHome alarm clock and it has glitches when I use my 3g but works well with my older 2g. Same thing with a sports watch I tested in the store. The TIMEX ironman watch that has wireless controls for the ipod didn't work with the 3g. So, if you are an early adopter, be aware of that. I'd recommend that if you have the 3g nano, that you test it carefully in the store with any product that claims to be 3g nano compatible before you buy and make sure the features you care about actually work.

According to the definition of Amazon Rating System, Please rate this text review.

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