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Assessing the effect of mobile word-of-mouth on consumers: the physical, psychological and social influences

Juanyi JIANG

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ASSESSING THE EFFECT OF MOBILE WORD-OF-MOUTH ON CONSUMERS: 
THE PHYSICAL, PSYCHOLOGICAL AND SOCIAL INFLUENCES

JIANG JUANYI

PHD

LINGNAN UNIVERSITY

2016
ASSESSING THE EFFECT OF MOBILE WORD-OF-MOUTH ON CONSUMERS:
THE PHYSICAL, PSYCHOLOGICAL AND SOCIAL INFLUENCES

by
JIANG Juanyi
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A thesis
submitted in partial fulfillment
of the requirements for the Degree of
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Lingnan University

2016
ABSTRACT

Assessing the Effect of Mobile Word-of-Mouth on Consumers: The Physical, Psychological and Social Influences

by

JIANG Juanyi

Doctor of Philosophy

Mobile technologies enable users to discover and research products anytime, anywhere. Mobile devices allow consumers to create and share content based on physical location, facilitate seamless interactions, and provide context-relevant information that can better satisfy users’ needs and enhance their shopping experience. As consumers increasingly rely on mobile devices to search information and purchase products, they need immediate, updated, informative and credible opinions in concise forms. Meanwhile, marketers face unprecedented opportunities for mobile marketing, making it ever important for them to understand the mobile word-of-mouth and its effect on the purchase behaviors of consumers on the mobile platform vs. those on other devices. Drawing from the media richness theory and the principle of compensatory adaptation, study one performs sentiment analysis of online product reviews from both mobile and desktop devices by analyzing over one million customer reviews from Dianping.com. We find that mobile reviews are naturally shorter, contain more adverbs and adjectives, and have smaller readership and less votes of helpfulness. The product ratings from mobile reviews are more polarized yet the average valence of mobile reviews is higher. By comparison, desktop reviews contain more pictures and are rated more helpful. Lastly, pricy products receive more desktop reviews than mobile ones. Study two draws from the construal level theory and posit that WOM from mobile devices reflects closer psychological distances (temporal and social), thus constitutes a lower construal level than that from desktop computers. Using a dataset of over one million product reviews from Dianping.com, we assess the value of online product reviews from mobile devices in comparison with those from the desktop computers. Our findings show that WOM is more helpful when it is socially and temporally closer to the users and this effect is amplified when using mobile devices, which bring the mental construal to a low level and make others’ opinions more relevant. Further, we show that product type moderates the effect of online reviews in that m-WOM is more
influential for hedonic products and its value for the utilitarian consumption is the lowest.

Study three deploys the observational learning theory to examine the effect of WOM across the mobile and desktop devices on the purchase behavior of online promotional offers. The findings suggest that the effect of WOM on the purchase of promotion offers varies significantly across the platforms, product categories, and discount rates. These findings help better understand the strengths, limitations and the effect of m-WOM as marketers attempt to offer consumers context-sensitive and time-critical promotions through mobile devices and make a significant contribution to the literature on interactive marketing. These studies render meaningful implications for theory development about the role of mobile technologies in marketing and can assist practitioners formulating effective promotional strategies through the electronic channels via mobile and desktop devices.

Keywords: WOM, m-WOM, Mobile Marketing, Media Richness Theory, Compensatory Adaptation, Construal Level Theory, Observational Learning, Online Promotion
DECLARATION

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

______________________________
(JIANG Juanyi)
Date:
CERTIFICATE OF APPROVAL OF THESIS

ASSESSING THE EFFECT OF MOBILE WORD-OF-MOUTH ON CONSUMERS:

THE PHYSICAL, PSYCHOLOGICAL AND SOCIAL INFLUENCES

by

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## TABLE OF CONTENT

**Chapter 1 Introduction**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1 Background</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Definition of Problems</td>
<td>2</td>
</tr>
<tr>
<td>1.3 Mobile Usage and Media Psychology</td>
<td>6</td>
</tr>
<tr>
<td>1.4 Mobile Usage and Psychological Distance</td>
<td>7</td>
</tr>
<tr>
<td>1.5 Mobile Usage and Social Network</td>
<td>8</td>
</tr>
<tr>
<td>1.6 Contributions and Implications</td>
<td>9</td>
</tr>
<tr>
<td>1.7 Organization of the Dissertation</td>
<td>10</td>
</tr>
</tbody>
</table>

**Chapter 2 Literature Review and Research Framework**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.1 Word-of-Mouth</td>
<td>12</td>
</tr>
<tr>
<td>2.1.1 Definition</td>
<td>12</td>
</tr>
<tr>
<td>2.1.2 WOM and Its Own Matrix</td>
<td>13</td>
</tr>
<tr>
<td>2.1.3 WOM and External Factors</td>
<td>14</td>
</tr>
<tr>
<td>2.1.4 WOM and Its Influence</td>
<td>15</td>
</tr>
<tr>
<td>2.2 Mobile Commerce</td>
<td>16</td>
</tr>
<tr>
<td>2.2.1 Definition</td>
<td>16</td>
</tr>
<tr>
<td>2.2.2 Consumer Acceptance</td>
<td>17</td>
</tr>
<tr>
<td>2.2.3 Summary</td>
<td>19</td>
</tr>
<tr>
<td>2.3 Research Framework</td>
<td>19</td>
</tr>
<tr>
<td>2.3.1 The First Level</td>
<td>19</td>
</tr>
<tr>
<td>2.3.2 The Second Level</td>
<td>20</td>
</tr>
<tr>
<td>2.3.3 The Third Level</td>
<td>22</td>
</tr>
</tbody>
</table>

**Chapter 3 Research Design and Methodology**

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1 Study One: A Comparative Study of WOM</td>
<td>23</td>
</tr>
</tbody>
</table>
3.1.1 Introduction ........................................................................................................23
3.1.2 Literature Review ..............................................................................................23
3.1.3 Theoretical Background ....................................................................................27
3.1.4 The Conceptual Model ......................................................................................30
3.1.5 Empirical Analysis ............................................................................................37
3.1.6 Conclusion ..........................................................................................................43
3.2 Study Two: The Value of m-WOM in Terms of Its Helpfulness .......................45
  3.2.1 Introduction ........................................................................................................45
  3.2.2 Literature Review ..............................................................................................46
  3.2.3 Theoretical Background ....................................................................................53
  3.2.4 The Conceptual Model ......................................................................................54
  3.2.5 Empirical Analysis ............................................................................................57
  3.2.6 Conclusion ..........................................................................................................64
3.3 Study Three: The Effect of m-WOM on Deal Purchase ....................................67
  3.3.1 Introduction ........................................................................................................67
  3.3.2 Literature Review ..............................................................................................69
  3.3.3 Theoretical Background ....................................................................................72
  3.3.4 The Conceptual Model ......................................................................................75
  3.3.5 Empirical Analysis ............................................................................................78
  3.3.6 Conclusion ..........................................................................................................83

Chapter 4 Research Findings and General Discussion ...........................................86
  4.1 Summary of Findings ............................................................................................86
  4.2 Theoretical Implications .....................................................................................88
  4.2.1 Media Richness Theory and Compensatory Adaptation Theory ..................89
  4.2.2 Construal Level Theory ...................................................................................90
4.2.3 Observational Learning and Social Influence……………………………91

4.3 Managerial Implications ……………………………………………………92

4.4 Limitations and Future Research …………………………………………94

4.5 Conclusion……………………………………………………………………95

References………………………………………………………………………..97
LIST OF TABLES

Table 1: Data Collection of Study One..............................................................38
Table 2: Variables Definitions of Study One..................................................40
Table 3: Comparative Statistics of Study One...............................................41
Table 4: Mobile WOM Attributions (Fix Effect Model) .................................43
Table 5: Data Collection of Study Two............................................................57
Table 6: Variable Definitions of Study Two....................................................59
Table 7: Comparative Statistics of Study Two...............................................61
Table 8: Value of m-WOM Helpfulness (Tobit Model) .....................................64
Table 9: Data Collection of Study Three .........................................................79
Table 10: Variable Definitions of Study Three.................................................80
Table 11: Comparative Statistics of Study Three............................................81
Table 12: Effectiveness of Friend’s Adoption and Deal Sales (GLMM).............83
LIST OF FIGURES

Figure 1: Global Mobile Retail Commerce Revenue 2012 to 2018…………………………2
Figure 2: Yelp Number of Unique Mobile Visitors Q1’13 to Q4’15…………………………4
Figure 3: Yelp Average Monthly Mobile and Desktop Visitors Q4’12 to Q4’15………5
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Thirdly I have to pay tribute to Dianping.com, they are my primary resource of data and what they’ve provided from inside is a price asset that helps me crank out this thesis, makes my research ideas valid and justifiable.
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Thank you

Joy Jiang
Chapter 1

Introduction

*We become what we behold. We shape our tools and then our tools shape us.*

-- *Marshall McLuhan*

1.1 Background

Has this ever occurred to you? You just had dinner at a restaurant and the experience was so incredible that it has to be shared when the feelings were still lingering in your mind. “This unidentifiable paste coats your mouth until you can’t perceive textures or flavors. It’s like edible Novocain”; “The desserts are orgasmic”; “The fois-gras on the plate was just seductively seared”. These are all come from the fingertips of a patron using his/her mobile phone while the waiter was cleaning the table.

Whatever customers might say about the product or business; business owners now need to consider the platform when evaluating the review content. It could be the effect of the device, which may or may be based on the actual quality of the product or service. If there is a sudden increase of short reviews in large quantities, it is probably because more and more of your customers are using mobile devices to write and post their reviews. Businesses today have a new channel to observe and monitor consumer behavior. Mobile phones and portable devices make it easy to do so many things on the go, including posting reviews of their consumption experiences instantaneously online. Moreover, the device that consumers are using greatly affect the way they...
search for information, make purchase decisions and communicate to others about their experiences. Given the ubiquity of mobile devices, managers need to have an in-depth understanding of their effects on customer communication and consumption behaviors to gain competitive advantage in the marketplace.

1.2 Definition of Problems

Mobile Internet traffic has surpassed desktop traffic in 2015; and the global mobile commerce sales are on pace to reach $298 billion in the same year (© Statista 2016). Undoubtedly, the mobile phone is one of the most popular communication platforms in the world. The development of mobile technology, wireless Internet, and social network sites have changed users’ behavior fundamentally. The anytime-anywhere services offered through these ubiquitous devices have great potential to provide consumers with an enhanced, more convenient and effective shopping experience, allowing them to create and share content based on physical location, facilitate a seamless interaction, and provide contextually-relevant information that help marketers better understand and satisfy users’ needs (Lee 2005).

Figure 1: Global mobile retail commerce revenue from 2012 to 2018
However, mobile devices have smaller screens. The limitation of small display capability of these devices and system response time affect the viewing and searching process of consumers. Not only the physical size matters, the irreversible habits that consumers gained through the technology are also changing at the behavioral and psychological levels. The demand for instant results is seeping into every corner; consumers have a need for immediacy and expect the updated, informative, credible and valuable opinion in an extract form.

Word-of-mouth (WOM) has been defined as informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services or their sellers, (Westbrook 1987). It is recognized that WOM has an important impact on consumers’ attitudes and purchase behavior because people are far more inclined to trust peer reviews than the information and assurances by businesses owners. They tend to rely on credible, neutral sources to make their decisions (Anderson 1998). The mobile technology has led to a proliferation of applications that provide consumers with temporal and locational dependent information to make choices and evaluations. The combination of mobile devices and social network services allow users to publish information without the constraints of time and space. Therefore, mobile word-of-mouth (m-WOM) is defined as gathering, transmitting, or retransmitting WOM through mobile devices. Examples include the ability to read and write reviews of restaurants on Yelp during dining, and to send real-time critics in Rotten Tomatoes while watching a movie.
Compared with PC, m-WOM communication may happen right at the time of purchase. People are able to publish their statuses, photos, and reviews online right after or even simultaneously at the time of consumption. It provides consumers with a portable and flexible means of disseminating and accessing information. In this regard, m-WOM overcomes the shortcomings of electronic word-of-mouth communication and helps marketers realize the full potential of marketing strategies by offering consumers with context-sensitive, location-relevant and time-critical recommendations. M-WOM may be also more revealing by providing managers the real-time feedback on service quality and help to respond quickly to address any issues because they are more likely to reflect an accurate picture of consumers’ service experiences than desktop reviews.

From the industry’s perspective, consumers are increasingly turning to apps when using their mobile phones. The number of mobile unique visitors at Yelp surpassed that of desktop visitors for the first time last quarter, solidifying the company's status in the mobile search space (© Statista 2016). The timeline in Figure 2 shows the number of unique mobile visitors of Yelp from 2013 to 2015 on a quarterly basis. Figure 3 presents the comparison of number of visitors from two portals; it clearly reveals the steady growth on mobile portal while the trend on desktop is relatively flat.

**Figure 2: Yelp Number of unique mobile visitors Q1’2013 to Q4’ 2015**
Although the importance of m-WOM seems obvious and is frequently emphasized, research on this topic is relatively scarce. There is substantial debate over the pros and cons of encouraging consumers to write real-time reviews with some fearing that mobile reviews will not benefit from in-depth reflections and that consumers will be rather emotional in responding to their current experiences. On the other hand, m-WOM tends to be written in real-time, whereas desktop reviews are written after the fact, resulting in what psychologists refer to as the “rosy retrospection” (Mitchell, Terence R., et al 1997). When consumers think retrospectively about something—while composing a review on their desktop, they tend to cast an experience in a blurrier light. Due to this concern, some review sites (e.g., Yelp) allow people to start reviews on their mobile devices but require them to use a desktop computer to finish them, a requirement that has since been discontinued.

The rapid change in mobile capabilities and usage presents challenges for both researchers and industries in understanding why and how people use mobile devices. The impact of technology is not in the tools themselves, but about the behaviors that
the tools facilitate. However, it is unclear how mobile WOM is different from those
from desktop devices. Thus, this research will be built upon the research of WOM and
studies of mobile technologies to assess the strengths, limitations and the effect of m-
WOM on consumer perceptions and purchase decisions by addressing these questions:
1) How do they differ in content? 2) What mechanisms drive these differences? 3)
How do they differ in helpfulness? and 4) How do they affect purchase behaviors?

1.3 Mobile Usage and Media Psychology

The first factor that causes the difference between mobile and traditional e-WOM is
that the devices used to convey mobile WOM is completely a new medium. We are
now increasingly use mobile devices to produce and read content that previously
existed on stationary screens. But this new medium is different, with smaller keyboards
and screens. These features increase the cognitive and physical costs associated with
using these devices (Lurie, Song, and Narasimhan 2009). At the same time, these
features also increase device accessibility as consumers carry mobile devices wherever
they go.

It was not so long ago that mobile devices were not even seen fit for proper content
creation or consumption. Writing text on a portable device remains as inconvenient as
taking pictures with our desktop webcam. However, nowadays, we are already doing
a lot from this device: add short but insightful comment, take on-site pictures and 1-
click sharing. Yet the user-generated content (UGC) on the mobile platform tends to
be simple, animated, narrative and less edited, the greater accessibility increases the use of mobile devices in low-motivation contexts. That is, small keyboards make it difficult to engage in extensive communication, but the frequency of doing so is increased. They are likely to be used to reflect instant reaction about consumption experiences.

Another factor that affects the content of mobile WOM is the stronger ownership and attachment between mobile devices and their users. Unlike desktop computers, mobile devices are usually used by individuals. They are an extension of the self (Rohm and Sultan 2008). In particular, the ability to customize apps, wallpaper, ringtones, cases, and other features make mobile devices reflections of ourselves (Sultan and Rohm 2005). The constant physical presence of mobile devices leads to strong emotional and psychological connections between devices and users (Turkle 2008). To the extent that mobile devices involve personal and autobiographical thoughts, mobile WOM should involve more use of emotional and self-expressive language than desktop devices would foster.

1.4 Mobile Usage and Psychological Distance

Psychological distance plays a fundamental role in affecting people’s self-image congruity and normative influence. Ubiquitous mobile devices are shifting our sense of psychological distance by allowing users to engage in activities in diverse physical locations, to access resources specific to the time, and to communicate directly or
indirectly with others. As the use of mobile technology becomes prevalent, it is crucial to understand how the state of mobility affects consumer’s perceptions and judgments. Although works on construal levels have traditionally examined the mental representation of future events (Trope and Liberman 2003), more recent research suggests that the effects of psychological distance apply in similar ways to retrospective evaluations (Trope and Liberman 2010). As for this study, creating m-WOM during or shortly after user experiences should reduce the psychological distance, both temporally and spatially between the two events. This means that mobile WOM should reflect a lower construal level than desktop WOM, as shown by a greater focus on current (rather than past or future) concerns. How the psychological distance induced by using mobile devices will affect the WOM and behaviors of consumers warrants investigations.

1.5 Mobile Usage and Social Network

The increasing ubiquity and easy access of mobile technology have dramatically increased user engagement with new platforms for social interaction. Given the increasing attachment to mobile devices and sharing of content with others, marketers have become keen to understand how consumers’ personal social networks affect the generation and consumption of mobile content.

On a theoretical level, past work has explored how social tie impacts individual behavior across several contexts (e.g., Granovetter 1973, Uzzi 1997). In general, the impact of tie strength is explained through its effect on the level of information that
individuals have access to, and network density is a measure frequently used to summarize how direct contacts in an individual’s personal network are connected to one another. Both tie strength and network density significantly impact individual’s interaction frequency and quality, in that strong ties (e.g., close friends that a focal user frequently interacts with) are more contagious while individuals with dense social networks are less susceptible to social contagion (Ghose, Han, and Iyengar 2013).

In our research, we explore whether this interpersonal factors have the “platform/medium” effect and affect the content generation and consumption by using mobile devices.

1.6 Contributions and Implications

Mobile word of mouth is created in real-time using devices that are both harder to use than traditional desktop or laptop computers; yet mobile devices are more accessible and more personal. For marketers, this research provides important insight into how increased use of mobile platforms is likely to lead to differences in the characteristics and influence of user-generated content (UGC). Our studies suggest that it is important to understand how real-time creation, small size issue, personal user-device ties and lower construal level are likely to change the content and value of mobile word of mouth. It is certain that people are moving to a mobile world, and technology is changing very quickly. People will continue to share their experiences, and it will go beyond a text review to video content in the future. One thing that marketers should assume is that consumers will be monitoring their experiences with increasing
frequency and surreptitiously sharing those experiences with others. Marketers who seek to understand and capitalize on this new content need to account for these changes.

Our work will contribute to the understanding of how mobile technology shapes WOM and how to utilize this distinct advantage in an environment where every interaction has the potential to be seen by others. For example, m-WOM uses language that is shorter and more emotion-driven. From this perspective, mining mobile word of mouth may be more influential for products and services in which real-time responses are desired. They provide a way for managers to get real-time feedback on service quality and to respond quickly to address those issues, because they tend to be written during or shortly after the consumption experience, therefore represent a more accurate picture of service experiences than desktop reviews. Moreover, by using mobile device, the construal level is lowered, thus such content will be more influential than that reflect a higher or more distant level. While m-WOM may be more volatile and capricious, which may not be persist in reflecting long-term attitudes, it will also help boom sales and stimulate consumption in a short time span.

1.7 Organization of the Dissertation

The dissertation consists of three studies to address the above questions. The first study includes text analysis of m-WOM. Using secondary data from a major review website in China, we compare the reviews from desktop computers and mobile phones in terms of their length, valence, and the number of readings. Drawing on the media richness
theory, the principle of compensatory adaptation, we posit that mobile reviews are shorter, more exaggerated and more subjective, thus resulting in more extreme ratings. The limited cognitive resources of m-reviewers lead to impulsive and polarized patterns that may cause difference and systematic bias when compared with those from the desktop PCs. In the second study, we empirically examine the effect of m-WOM on consumers by incorporating the contextual variables of social relationship and time contiguity. We investigate whether m-WOM is more helpful to consumers with a closer social network relationship than those from a distance, and whether it has a “recency” effect. In study three, we extend these attributes into examining the relationship between m-WOM and actual consumption behavior by investigating the dynamic effectiveness of promotional deal adoption.

The remainder of this dissertation is organized as follows. The next section provides a literature review covering the mainstream of WOM and mobile studies. This is followed by three studies to test the hypotheses. The last section summarizes the key findings of these studies, highlights both theoretical and managerial implications and future research directions.
Chapter 2

Literature Review and Research Framework

Overview

Although the studies of mobile topics are abundant, only recently have authors investigated how consumers use mobile devices for commerce related activities. Most of them adopt the technology acceptance model to understand the consumer perception of their usage experience (Davis 1989; Venkatesh & Davis 2000). For this dissertation, the interesting problem is how the features and the mobility of the device affects the types of content people are likely to create and share and how these factors further shape the consumption behavior.

The following literature review examines the research in the areas of word-of-mouth, and mobile commerce, including theoretical development and empirical studies. The intersection of these areas lay the foundation for examining effect of m-WOM in terms of its characters and effectiveness.

2.1 Word-of-Mouth

2.1.1 Definition

Word-of-mouth (WOM) refers to oral, person-to-person communication between a communicator and a recipient who perceives the respective message as a non-commercial although the subject is a brand, product, or service (Arndt 1967). It is long
perceived as an important and convincing endorsement, from the old proverb's wisdom “Let another man praise thee, and not thine own mouth; a stranger, and not thine own lips” to now-a-day’s online marketing. Since the early 1950s, researchers have shown that WOM not only influences consumer choices and purchase decisions (Katz and Lazarsfeld 1955), but also shapes pre-usage attitudes (Herr et al. 1991) and post-usage perceptions of a product or service (Bone 1995). Recently, with the prosperity of Internet, online Word-of-Mouth regains its attention from researchers in marketing, information systems, and computer science. In fact, online-WOM is now the primary factor behind 20% to 50% of all purchasing decisions, according to the recent McKinsey & Company’s report. Social media has transformed WOM from being a ‘one-to-one’ to a highly lucrative ‘one-to-many’ marketing model, where a single product review posted online or disseminated through social networks can reach millions.

2.1.2 WOM and its own Matrix

The majority of recent research in WOM’s attributes focused on valence, variance, and volume (Dellarocas and Narayan 2006). Valence is represented by an average rating measure (Chevalier and Mayzlin 2006; Dellarocas, Zhang, and Awad 2007; Duan, Gu, and Whinston 2008). It has also been represented by some measure of positivity or negativity of ratings (Liu 2006). The variance is measured from a statistical variance (Clemons, Gao, and Hitt 2006) representing consumer taste or product familiarity (He, Stephen X, and Bond 2015). Volume is commonly measured by the number of postings.
The elasticity of the volume versus valance and variance study represents the interplay between these aspects and offers numerous directions for future research in the area (You, Vadakkepatt, and Joshi 2015). The rationale behind study these metrics of online product reviews is that these stand for the general perceived quality, popularity and the controversial opinions of the products among consumers.

2.1.3 WOM and External Factors

Even when the information is the same, the difference in information context can bring a significant impact on the consumers’ evaluation. In other words, receiver’s perception on a given piece of WOM can be vary. Some research suggests that the perceived value of consumer-created content depends on the external factors, such as posters’ prior posting behavior, their expertise and the presence of temporal distance that connect word-of-mouth to product experiences (Chen and Lurie 2013; Forman, Ghose, and Wiesenfeld 2008; Weiss, Lurie, and MacInnis 2008).

Another significant external factor that may contribute to the perceived effectiveness of WOM is the type of product or the service they are discussing. Prior research classified consumer products into two types based on a criterion whether consumers can obtain enough information on the product before purchasing (Klein 1998). Product descriptions of experience/ hedonic products might not provide satisfactory information, and it is often the case that the quality of the product can be inconsistent, like restaurant businesses. On the other hand, the reviews of utilitarian products tend to be instrumental and practical. Whether the information about the dominant
attributes of a certain product or service can be accurately presented affect the influence of WOM, because online transactions of hedonic goods tend to involve more uncertainties than that of utilitarian products which involves more rational thinking (Hu et al. 2008). As such, the creation and effectiveness of WOM vary across different product types.

2.1.4 WOM and Its Influence

There is growing evidence that consumers are influenced by online WOM when making a variety of purchase decisions (Cui, Lui, and Guo 2012; Sen and Lerman 2007; Senecal and Nantel 2004; Sawhney and Eliashberg 1996). Therefore, WOM’s studies have been extended to a broader territory from why it works to how it works. The research including: the usefulness and helpfulness of online product reviews for consumer decision making (Smith et al. 2005); the value of online consumer reviews for sales forecasting (Dhar and Chang 2009); the consumers’ motivations for posting online product reviews (Hennig-Thurau et al. 2004; Chen et al. 2011); and product-specific attributes that would be greatly affected by online reviews (Zhu and Zhang 2010).

As WOM has become one of the most important sources of information for various services in ever-growing popular social networks, it is also turning into a kind of virtual currency for businesses looking to market their products, identify new opportunities, and manage their reputations.

With the growth of mobile technology and the usage of mobile devices by consumers,
there is substantial debate over the pros and cons of encouraging consumers to write real time reviews. Some fear that mobile reviews will not benefit from in-depth reflections and that consumers will not objectively respond to their consumption experiences. Others are concerned that the aggregation of m-WOM will cause the systematic bias and lead to diminishing value of consumer reviews. However, it is not yet clear and certain whether these concerns are justified.

2.2 Mobile Commerce

2.2.1 Definition

The study of m-WOM is a tip of the iceberg of a broader concept of mobile commerce. Mobile commerce refers to the use of wireless technology, particularly handheld mobile devices and mobile Internet, to facilitate transaction, information search, and user task performance in business-to-consumer, business-to-business, and intra-enterprise communications (Chan and Fang 2003). It was not so long ago that the research of these issues was just at the exploratory stage. The researchers began with the conceptualizations and differences between e-commerce and m-commerce, the dimensions of mobile market place, key features and unique value propositions of the mobile medium (e.g., ubiquity, convenience, personalization, localization, flexibility, spontaneity, immediacy, accessibility, time-criticality and instant connectivity). Researchers have proposed several frameworks for the study of m-commerce. One of them presents 12 classes of m-commerce applications, ranging from retail and online shopping, auction, mobile office, and entertainment to mobile inventory, emphasizing
the potential of mobile-commerce can be unlimited (Varshney and Vetter 2001). The other one in the same year categorized mobile commerce into goods, services, content for consumer e-commerce, and activities among trading partners (Kannan, Chang, and Whinston 2001).

It was once argued that the mobile, wireless channel should be viewed as an extension of the e-commerce channel or as part of a company’s multi-channel strategies for reaching customers, employees, and partners. Major e-commerce sites indeed have implemented their mobile internet sites as an extension of wired e-commerce to support existing customers (Chan and Lam 2004). However, recently, a more radical view suggests that m-commerce can create its own markets and business models and offer new applications to business and consumers (Coursaris and Hassanein 2002). It suggests that in a multi-channel environment, m-commerce enriches e-commerce instead of becoming a substitute for e-commerce. Enterprise and business applications of m-commerce hold greater promise, because it is easier for companies to fully utilize the contextual and environmental support to improve current work processes.

2.2.2 Consumer Acceptance

The value of mobile devices is based on their distinctive features, especially its personal and the intimate nature, because it is “always with the user”, “always on” and “always connected”. Its unique characteristics result in different consumer attitudes. Recent researchers examine the factors affecting consumer attitudes and usage behavior in respect to mobile content. Four main constructs: entertainment,
information, irritation, credibility, and two other factors: permission and incentive are included in the attitude framework, (Tsang, Ho, and Liang 2004)

Building on theory of reasoned action (Fishbein and Ajzen 1975), theory of planned behavior (Ajzen 1985), technology acceptance model (Venkatesh and Davis 2000), innovation diffusion theory (Rogers 1983) and theory of use gratifications, empirical studies suggest that both utilitarian value (Bauer et al. 2007; Kleijnen, Ruyter, and Wetzels 2007) and hedonic value contribute to consumer adoption of mobile content but the influence of hedonic value is stronger when compared to utilitarian value in building attitudes towards mobile technology in general.

Besides the content itself, the consumer acceptance is also likely to be influenced by their own personal predispositions, tendencies, attitudes and individual-level perceptions (Junglas, Johnson, and Spitzmüller 2008; Khalifa and Shen 2008) and their demographics (Bigne, Ruiz, and Sanz 2005).

Other researchers have examined the external factors that influence the consumer acceptance on mobile content, such as social/peer influence (Lee and Murphy 2006; Newell and Meier 2007), the relevance and the credibility of the content (Haghirian and Inoue 2006; Okazaki 2004), the level of trust towards the message sender (Lee, 2003; Lin and Wang 2006; Lu, June et al 2004; Luarn and Lin, 2005; Okazaki, Katsukura, and Nishiyama 2007; Zhang and Mao 2008), the context of the message (Barnes and Scornavacca 2004; Karjaluoto and Alatalo 2007; Knutsen 2005;), the geographical location (Molitor 2012), and user control over content, delivery timing
and frequency (Carroll et al. 2007; Maneesoonthorn and Fortin 2006). These all suggested that the mobile acceptance and effectiveness is subjected to both content attributes, users’ own experience and contextual environment.

2.2.3 Summary

The above review of the literature provides the landscapes of research in both WOM and mobile commerce, regarding their definition, nature, value and effectiveness. Our following research will integrate these two areas and focus on examining the content characteristics of m-WOM and its effects. Up to date, there have been few studies of how consumers use mobile devices to search and communicate information or compare the effect of mobile content with that from the non-mobile devices.

2.3 Research Framework

2.3.1 The First Level

The conceptual framework of this dissertation has three levels. The first level focuses on the characteristics of m-WOM. Several theoretical perspectives shed light on the mobile WOM in comparison with those from non-mobile devices. Here we mobilize compensatory adaptation and media richness as our theoretical background to study the consumer reviews on the mobile platform. The theory of media richness states that the more ambiguous and uncertain a task is, the richer the format of media that suits it. It is based on the contingency theory and the information processing theory. They propose that communication media have varying capacities for resolving ambiguity
and facilitating understanding. Compensatory adaptation theory, however, suggests that people tend to take measures to compensate for the shortcomings of certain media or devices (Kock 1998, 2001). It provides an alternative theory that could overcome the limitations of the media richness theory that the inadequacy of media can be compensated by the user and device itself.

The field of cognitive and media psychology generally regards cognitive capacity and indirect media communication as a limited resource, which affect people’s creation as well as their comprehension of a message (McCutchen 1996). We expect that the smaller size and mobility exert a significant influence on people’s cognitive resources and strongly affect the attributes of mobile product reviews. Therefore, in the first study, we will compare the WOM from different portals in terms of their content, valance, volume, variance, their contributors (reviewers) and the type of product.

2.3.2 The Second Level

The second stage of the framework examines on the perceived value and helpfulness of m-WOM, and its effect under the influence of social and temporal distances. The construal level theory (CLT) describes an account of how psychological distance influences individuals’ thoughts and behavior. CLT assumes that people mentally construe objects that are psychologically near in terms of low-level, detailed, and contextualized features, whereas at a distance they construe the same objects or events in terms of high-level, abstract, and stable characteristics. According to CLT, different dimensions of psychological distance (time, space, social distance, and hypotheticality)
affect mental construal and that these construals, in return, guide prediction, evaluation, and behavior. Individuals use concrete, low-level construals to represent near events and abstract, high-level construals to represent distant events. Low-level construals are relatively unstructured, contextualized representations that include subordinate and incidental features of events. High-level construals, in contrast, are schematic, decontextualized representations that extract the gist from the available information (Trope and Liberman 2003).

Construal level theory has recently been extended to the research of mobile users’ behavior. In the second study, we analyze the circumstances in which m-WOM are more valued. The distinctions between self and others, similar and dissimilar others, or in-group and out-group members are all instances of social distance (Trope et. al 2007). Prior research has consistently shown that distal social targets (e.g., others or out-group) are construed at a higher and more abstract level than a proximal social target (e.g., self or in-group) (Kim, Zhang, and Li 2008; Jones and Nisbett 1972).

Relating these findings to recommendations made by peers in product evaluation, they conclude that other people’s recommendations are represented at a higher and more abstract level while words from friends are construed as a concrete and low level. Different temporal construals also differ in the extent to which they are associated with positive or negative event evaluations. Recent recommendations are perceived to be more convincing since they reflect the true pictures of the present moments. Our second study will test whether the immediacy and a closer tie relation will affect the
perception of reviews and whether such perception vary across different portals.

2.3.3 The Third Level

The third level of framework focuses on the m-WOM’s effect on online promotion adoption. Those promotional deals are often offered by new merchants or about new products that they are promoting. Consumers are usually uncertain and suspicious of the actual deal worth but may still attracted by the discount.

The third study is grounded in the Observational Learning, Social Influence theory and Construal Level Theory, which posit that people follow others’ actions when they are able to observe them (Bandura 1977; Cai, Chen, and Fang 2009). In the promotional deal setting, consumers may find it difficult to ascertain a deal’s worth because deals are experience goods often promoted by new merchants (Wang, Zhao, and Li 2013). Yet through observation, consumers can update their imperfect information by observing deal popularity, deal worth or the cumulative number of deals sold to preceding peers. Real-time word of mouth of the deals is an indication of how other consumers evaluate a deal offer, it can signal deal worth and influence a focal consumer’s purchase decision. The observation of this action-based behavior may boost consumer arousal and confidence regarding the deal, both of which affect purchase likelihood. Hence, we test and compare the WOM’s effectiveness on actual adoption of these promotions from both portals and incorporate the findings of first two studies to examine the effect of these attributes in the stage of conversion or revenue generation.
Chapter 3

Research Design and Methodology

Study One: A Comparative Study of WOM on Mobile Devices and PC/Desktops

3.1.1 Introduction

The convenience of the social network and mobile technology drive people to search for other’s reviews of products or services right before the purchase, simultaneously generate their opinions even when they are still in the process of consumption. Our first study of mobile word-of-mouth focuses on their characteristics in comparison with that from desktop computers. The size and time limitations of the mobile devices put a significant constraint on people’s cognitive resources and affect the characteristics of mobile WOM.

In the following sections, we will review the literatures of consumer adaptation on mobile content and incorporate theories of media psychology, namely media richness theory and compensatory adaptation theory to study the features of the m-WOM and the key differences when compared with these from traditional desktop computer. By using the abundant data of restaurant and service rating website Dianping.com, we compare the content attributes from different platforms: desktop and mobile portal. Base on the empirical findings we will discuss the implications and extend them to our second and third study.

3.1.2 Literature Review

3.1.2.1 User Interface on Mobile Device
The content on the mobile device is evolving along with the development of user interface. Mobile technology can complement existing applications and infrastructure of data processing, communication, and notification by adding geographical and contextual information. However, mobile devices are typically smaller than their desktop counterparts, have less processing power, and communicate in low-bandwidth environments. Although people can now use a mobile application conceivably at anywhere at any time, smaller screens and changing environmental conditions (brightness, noise levels, and weather) affect the usage convenience and their attention span. Lee and Benbasat (2003) proposed an extended framework for user interface of mobile platform. They emphasize that, because of the unique characteristics of the environment and device constraints in mobile applications, the interface and message it conveys must consider context, content, community, customization, communication, connection and mobile device constraints. Lamming et al. (2000) also argue that mobile devices enrich the communication between users by providing users with an easy method to exchange information. Therefore, a set of mobile friendly design is created to both compensate the limitation and enhance the advantage of mobile device: on-site check-in to indicate the location; one click photo taking and sharing to simplify the posting process; 140 words content for easy typing and reading under a lower cognitive attention, etc. These new adaptations make the posting and sharing word-of-mouth effortless and spontaneous.

3.1.2.2 Content Generation and Reading on the Mobile Device
The terms “computer-mediated communication” (written text formulated on or conveyed via the internet on computers) and “electronically-mediated communication” (including mobile platforms) have been studied in the literature (Baron, N. S 2013). Linguistic shortenings (e.g., abbreviations and acronyms), online discourse, or differences between content characteristics are drawing more attentions. Here we define a mobile platform as any device someone can easily carry while stay connected to the Internet. This definition includes tablets and mobile phones.

Key factors shaping language use on these new media involve functionality and mobility, including the input system (e.g., multi-tap or virtual keyboard) and suitability of the screen for reading (e.g., visual clarity, screen size, proportion of space) (Baron, N. S 2013). Most mobile devices have decreased text length, given input challenges. Keyboards on a smartphone are not convenient to writing lengthy text. As users shift to mobile platforms on which text production is more cumbersome than on full keyboards, content generation is also affected.

Research on language produced or conveyed on new media has centered on the text appearing on screens (Crystal 2001). Relevant production variables include: language and writing style (e.g., spelling, punctuation, editing); length of content conveyed; mode of reading (e.g., skimming, use of search function, deep reading); length of text read; reading speed and memory for recall the content. The relevance of text length (already a challenge on a computer screen) is heightened as screens become smaller and potentially more difficult to annotate. New questions include what kinds of texts
are suited for mobile reading (e.g., news stories or restaurant reviews, but not a fiction); the demand for instant access to news, current events or personal online social connections; how people read and evaluate reading on screens that are comparatively large (computers, laptops) and small (mobile phones). Early studies (Dillon 1992) compared how well consumers read from computer screens. Under the perspectives of cognitive psychology, others have examined how small size screen affect content generation and reading behaviors (Garland and Noyes 2004; Noyes and Garland 2006, 2008). They conclude that time pressure and tradeoffs between physical and cognitive effort on mobile phones have lead to important differences in content, potentially affecting the usefulness of the content (Lurie et al. 2009).

3.1.2.3 Behavioral Evolution on Mobile Device

Consumers are using their mobile devices to access content everywhere they go, and so the digital environment is constantly changing to accommodate this consumer behavior. Researchers have studied the behavior of media shifting (from fixed desktop to mobile device) including writing, reading and unique using pattern. Recently, the implications of mobility have attracted the attention of communication researchers (Donald, Anderson, and Spry 2010; Katz 2008; Rainie and Wellman 2012). However, most of them have not examined the device-specific variations. There is an emerging stream of literature on behavior differences between the desktop and mobile device. For example, Ghose and Han (2011) find that there is a negative and statistically significant temporal interdependence between content generation and
usage on the mobile Internet. Ghose et al. (2012) explored how Internet browsing behavior varies between mobile phone and PC users in a natural experimental setting. They show that search costs are higher and the benefit of browsing for geographically close matches with retail stores is higher on the mobile platform when compared to the PC.

In the following section, we will begin with the investigation of how consumers adapt to the mobile platform content under Media Richness Theory and Compensatory Adaptation Theory, and then present a framework of comparative study.

3.1.3 Theoretical Background

3.1.3.1 Media Richness Theory

Media Richness Theory (MRT) is a framework to describe a communications medium by its ability to reproduce the information sent over it. This theory states that a medium is capable of sending rich information (i.e., text, smell, pictures, noise, etc.) and proposes that media usage is the most adequate if the medium is matched with the complexity of the task at hand. The theory is mostly used in studying how and why people choose a certain medium to accommodate their communication needs and evaluate the richness of certain communication media. It holds that when selecting communication media, individuals will do so depending on the level of equivocality or ambiguity. Rich media are believed to be appropriate for equivocal situations while lean media are appropriate for uncertain situations. Here richness is defined as the potential information carrying capacity (Daft and Lengel 1986). The information rich
media are more effective for complicated issues than leaner, less rich media. MRT proposes a hierarchy of information media based on information richness using four distinguishing factors: the feedback capability of the medium; number of channels used, personal or impersonal; and finally, language variety, such as verbal or non-verbal content. They suggest that media users play an active role in choosing and using the media, as they are goal oriented and always seek out a medium that best fulfills their needs.

However, Media Richness Theory has been found to have a number of shortcomings. First, the theory does not take into consideration the qualifications of the media user, and focuses only on qualities of the communication media (whether it is rich or lean). The theory does not explain the similar results in knowledge acquisition or the different levels of critical thinking that occur when using different media (Alavi et al. 1995). Finally, it was developed when a large portion of the media in use today was not yet in existence. Over a decade ago Dennis and Kinney (1998) and El-Shinnawy and Markus (1997) noted that media richness theory did not appear to handle preferences for “newer” media such as e-mail, Instant messaging, video chat and others. Most importantly, media richness theory does not incorporate any reference to biological and evolutionary explanations into a theoretical framework. From a more positive perspective, recent research on communication in e-commerce (DiClemente and Hantula 2003; Hantula et al. 2008; Rajala and Hantula 2000; Smith and Hantula 2003) and Internet information search (Pirolli 2007; Pirolli and Card 1999) has shown
clearly that an evolutionary perspective on electronically mediated behavior, which brings valuable insight for understanding how people interact with these new technologies.

3.1.3.2 Compensatory Adaptation Theory

To incorporate features of social and technological theories in an evolutionary perspective, Kock (1998, 2001) proposed media naturalness theory (also referred to as compensatory adaptation theory or CAT), a framework that combines evolutionary theory with social and technological theories to account for behaviors in electronic communication.

From an evolutionary standpoint, synchronous face-to-face communication, using primarily auditory sounds and visual cues, has been the primary mode of communication in the human history. This observation leads to the conclusion that the human biological communication apparatus is designed through evolution primarily for face-to-face interaction. The use of communication media that suppress certain face-to-face communication elements in order to solve problems created by modern society (e.g., instant messaging) and allows for non-co-located communication, is a recent phenomenon in evolutionary terms. Even though the use of electronic communication media increases cognitive effort and communication ambiguity, it has a neutral impact on outcome quality. According to the compensatory adaptation theory, individuals who are engaging in communication will attempt to and often succeed in compensating for them. As such, electronic communication media users can adapt
their behavior in such a way as to overcome some of the limitations of those media.

In summary, compensatory adaptation theory argues, in an apparently paradoxical way, that obstacles posed by electronic communication media will have no negative effect on the quality of outcomes as individuals engaged in communications attempt to (often involuntarily) and often succeed in compensating for their limitations. Since electronic communication media offer some advantages over the face-to-face medium, such as the possibility of asynchronous and non-collocated interaction, the compensatory adaptation theory supports the paradoxical notion that “less can be more”.

Nowadays, mobile devices are gradually taking over the fixed desktop computers as the primary vehicle of communication for everyday life: relationships, work communications, on-the-go shopping, searches for information, and management of the latest happenings and news. As consumers engage in more m-WOM, they grow accustomed to posting reviews and expressing their feelings for a certain consumption right after the experience. We posit that the richness of mobile as an information carrier affects how consumers compensate for its limitations.

### 3.1.4 The Conceptual Model

In the context of mobility, short attention span and limited cognitive resources are the major concerns for information processing. The above theories play help to explain the adoption of mobile word-of-mouth.

Review systems on mobile devices are lean due to the constraints of interface size and time. However, mobile devices certainly offer some advantages, such as instant
interaction and gratification. According to MRT and CAT, users try to exploit WOM through their mobile devices in several ways: (a) they take advantage of the immediate feedback (asynchronous) from other customers; (b) they use the variety of communication cues available, such as on-site check-in and photo posting and (c) the capability of language variety, which includes emotions in form of ‘smiley’ and the capability of ‘liking’ the comment made by customers. On the other hand, the exploitation of the richness of the mobile medium may be also constrained by the access and quality trade-off. Although the quantity of mobile reviews is achieving enormousness, the quality of them might be diluted due to the shortness and abstractness. In the following paragraphs, we will develop a set of hypotheses regarding the distinctiveness of the mobile review and test them empirically.

Firstly, the most important difference between mobile and traditional WOM is that the devices used to create mobile WOM tend to be smaller in size, with smaller keyboards and smaller screens. These factors increase the cognitive and physical costs associated with using these devices (Lurie, Song, and Narasimhan 2009). Researchers have noted that certain tasks are more difficult to achieve by using a simplified user interface, it makes the writing significantly more challenging (Ghose et al. 2013), thereby increasing user search costs and effort. In the context of online reviews, it translates into difficulty typing and navigating. Although mobile platforms of review system have already accommodated these issues, nevertheless, we maintain an expectation of reduced length when it comes to mobile reviews.
**H1: Reviews from mobile device are shorter than the ones generated on the desktop portal**

At the same time, the same factors (smaller size) increase device accessibility since they allow consumers to carry mobile devices wherever they go. It has often been noted that a major benefit of the mobile Internet comes in the form of convenience. This greater accessibility increases the use frequency and impulsivity. That is, although consumers will engage in WOM on both mobile and desktop platforms for experiences that are strongly positive or negative, they should be less likely to use mobile platforms for WOM about neutral experiences as the motivation to engage in such WOM is lower (Anderson 1998; Godes and Mayzlin 2004). In contrast, because mobile devices are always available, they are likely to be used to generate word of mouth at an impulsive moment (Novemsky and Ratner 2003). The ability to post a review on the spot, immediately following a consumption experience, might enable consumers to “rage” or conversely, “ecstatic”. If a consumer waits longer before posting their review, we might expect them to be in a calmer, cooler mindset, reflecting their experience more objectively. Reviews written during or immediately after service experiences should be more extreme than those retrospective reviews written on PCs. The greater likelihood of providing extreme WOM suggests that the distribution of mobile WOM will be more polarized, on average, than desktop WOM.

**H2: Ratings from mobile device are more polarized (extreme) than those generated on the desktop portal.**
Thirdly, we argue that mobile reviews likely contain greater emotional content than desktop reviews. This is fundamentally because mobile devices provide users with increased opportunity and access to the Internet, and thus enable impulsive, emotional actions, which would otherwise subside if the user were required to wait for a period before taking action (Loewenstein 1988; Loewenstein 1996; Loewenstein 2000). Mobile WOM is often created during or immediately following the consumption experience (Miller 2009). In particular, consumers increasingly tweet their real-time evaluations of movies and TV shows or evaluate the food as they are savoring it (Esparza, O'Mahony, and Smyth 2010). Desktop WOM, in contrast, is generally created long after the consumption, which is retrospective and involves memory retrieval about the experience. The real-time nature of mobile WOM has a number of implications about the characteristics of its content. Here, we anticipate that mobile reviews will be more likely to contain emotional textual content. Mobile consumers spend less time thinking about and processing their experiences before engaging in WOM but often project an extreme and impulsive reaction. Because it involves limited reflection, mobile WOM should involve more “hot” reasoning (Ariely and Loewenstein 2006) and therefore be more affective and less cognitive. Therefore, more emotions will be contained in m-WOM.

**H3: Reviews from mobile devices contain more affections and adverbs than those generated on the desktop portals.**

Because it is more likely to be created in real time, mobile WOM is less subject to
retrospective biases than desktop WOM, where retrospective evaluations are generally more biased than evaluations that occur during experiences. Biases in retrospective evaluations are observed when the to-be-evaluated information is presented sequentially or the to-be-assessed as an event unfolds over time. In order to assess an event in retrospect, people rely on their memory but in a way that is biased by the relative availability of certain features of the event. (Mitchell et al. 1997; Wirtz et al. 2003; Aldrovandi 2009). There are several lines of research on how memories and their effect change over time. Evidence from attitudes research suggests that evaluations could become diluted, especially the positive ones (Linville 1982; Millar and Tesser 1985; Wilson and Schooler 1991) over time as a result of many factors ranging from the complexity of the topic to the need for justification. A substantial body of work also deals with how people feel before or after an experience and suggest that retrospective evaluations may be based on current feelings (Ross, McFarland, and Decourville 1989). Hence m-WOM is less subject to the dilution of affective and positive feelings with the passage of time:

**H4: Ratings from mobile device are more positive than those generated on desktop device.**

Stronger personal relationship between mobile devices and their users is also likely to affect the content of mobile WOM. Unlike desktop computers, mobile devices are almost always used by a single individual and taken as an extension of self (Greenwood 2011). In particular, the ability to customize apps, wallpaper, ringtones,
cases, and other features make mobile devices as reflections of ourselves and provide ways to express ourselves to others. Phones no longer just connect us to people. As their features grow more complex, customizable, and personal, they connect us to ourselves. The constant physical presence of mobile devices leads to strong emotional and psychological connections between mobile devices and the users (Turkle 2008). To the extent that mobile devices foster personal awareness and autobiographical thoughts, content the user generates merely stands for personal subjective opinion and involves less use of “public comments.” This implies, by posting reviews on mobile, reviewers are expressing themselves rather than speaking to the public. However, to those opinion leaders and critics who live on those quality and objective reviews to maintain their high reputation, they need a fixed environment and a timely process to foster the reviews. Thus:

**H5: Mobile reviewers have less fans (followers) when compared with desktop reviewers.**

To extend the effect of social status, word choice in online restaurant reviews reveals much about people's inner thoughts, according to a Stanford researcher Jurafsky (2012) examine online reviews and the meanings that are hidden in the way people use words and connotations. He finds what a consumers tell us about restaurants is not only about the food, but also about who they are, the psychology of the persons who wrote the reviews.

Reviews of expensive service or goods often come from well-travelled customers who
are already exposed to higher qualities. To match the status of such consumption and adhere to their sophistication, they rely on complex words and crafty expressions to support their image, using words like "sumptuous," "commensurate," "unobtrusively" and "vestibule." It takes more time and cognitive efforts to generate such desktop word of mouth (d-WOM) on PCs, something that is hard to do in an on-the-go situation using mobile devices. Hence, we propose,

**H6: The products associated with mobile reviews are less expensive than those associated with desktop ones.**

In general, aside from being short and albeit less informative, we expect mobile WOM to be more concise and animated, using more extreme word expressions, in comparison with those written using non-mobile devices. The readers, who may also use mobile devices and surf online mostly have low motivation in reading. People just do not read every review; instead, they rely on the overall score awarded to the businesses or their rankings relative to others. In contrast, people will spend more time reading informative and well-crafted reviews, i.e., those generated from desktop PCs.

**H7: Reviews from mobile devices are read less than those generated on the desktop portal.**

Altogether, we examine the attributes of m-WOM namely: length, valence, variance, volume, extremeness and social status of reviewers as well as the product price level of those reviews are commenting on. We explore the characteristics of m-WOM and compare with those from desktop devices. The hypotheses in the conceptual
framework are tested by analyzing the secondary data collected from Dianping.com.

3.1.5 Empirical Analysis

3.1.5.1 Data Source

The data used in this study were retrieved from Dianping.com. Started in 2003, Dianping.com is an online site for restaurant reviews, ratings and group-buying, which is one of the leading consumer advice websites in China, covering local businesses in industries including dining, movies, entertainment, beauty, wedding, mom & kids, and home renovations, etc. According to the data from Alexa.com, Dianping.com has a global traffic rank 485th and a regional traffic rank of 82nd (in China). As an extension of its local information service to mobile platforms, Dianping.com launched a mobile Internet service in 2008, which is now surpassing the desktop traffic and accounted for 5/6th of the total traffic amount. As of second quarter in 2015, Dianping had more than 200 million monthly active users, over 90 million user-generated reviews, and more than 14 million local businesses in approximately 2,500 cities worldwide. Up-to-date, Dianping, including Dianping.com and their mobile applications, has more than 20 billion monthly page views, with over 85% page views from mobile users. We believe that Dianping.com is a suitable online review platform to test our research model. Choosing a single research site can help minimize the variation of reviews from different platforms.

3.1.5.2 Data Description

This study aims to determine the key characteristics of m-WOM and their unique attributes when compared with the desktop WOM. As indicated in Table. 1, we
randomly collected the review data for 6270 businesses in Shanghai (including branches), covering dining and car care service, from Jan 1 to Dec 31 2014, including those from both desktop and mobile devices. The dataset has a total of 1,048,575 reviews from 499,103 users on 6,270 businesses. Among them 744,759 reviews (71%) were written on mobile devices, while 303,816 (29%) were written on desktops. For each review, we record the attribution variables of both businesses, the reviews and reviewers to examine the content of mobile WOM.

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3.1.5.3 Methodology

To test the differences in language use for mobile versus traditional WOM, we first conduct sentiment analysis to identify the language and their lexical features of the review content. Following prior research (Berger and Milkman 2012; Ludwig et al. 2013), we process the full text of reviews using the Linguistic Inquiry and Word Count (LIWC) software program (Pennebaker et al. 2007). LIWC measures the percentage
of words in a given text that reflect particular linguistic or psychological processes, personal concerns, or spoken categories of language. It highlights each characteristic of the words used in the sentence and helps us to identify the tonality of it. It has been widely used for psychological text analysis, and its dictionary is the core. Since our data source and review content is mainly written in Chinese, we employ the analysis by using their Chinese dictionary. The Simplified Chinese version of LIWC dictionary is developed by National Taiwan University of Science and Technology based on the LIWC English dictionary (Huang C L, Chung C K, Hui N, et al. 2012). It includes 6,800 words across 71 categories and covers the official Chinese words both in written and spoken, network high frequency words are included as well. Hence, the Chinese punctuations are properly recognized and interpreted.

Hypothesis 1 refers to the length of online reviews; it is the character count of each text review. Hypothesis 2 refers to the extremity of ratings. We measure it in terms of a binary variable. Hypothesis 3 refers to textual indications of review sentiment. To capture this, we construct the variable affection and adverb from a series of vocabulary categories we distract from LIWC. Hypothesis 4 refers to the valence of reviews positivity. We measure review valence in terms of an ordinal variable, which can take whole integer values between 1 and 5. Hypotheses 5 refers to the reviewer’s social status among the network, we look at the reviewer’s number of fans on the platform. Hypotheses 6 is regarding the value of consumption; we use the average price of the business they are talking about as the indication. Lastly, Hypotheses 7 refers to the
readership of each review, we use the total number of hit they receive.

We provide definitions for all of our variables in Table 2 and comparative statistics of these variables in Table 3. Beyond the population-level statistics, we also break down the statistics between mobile and non-mobile reviews. Upon doing so, we already begin to see evidence that mobile reviews are significant different from non-mobile reviews; we observe statistically significant mean differences, generally in the anticipated direction.

Table 2. Variable Definitions of Study One

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portal</td>
<td>Independent</td>
<td>A binary indicator of whether the review was entered via a mobile device. 1 stands for mobile; 0 stands for desktop.</td>
</tr>
<tr>
<td>Length</td>
<td>Dependent</td>
<td>A positive integer value representing the number of characters in the body of the review.</td>
</tr>
<tr>
<td>Extremity</td>
<td>Dependent</td>
<td>A binary indicator of whether the rating's valance is extreme, positive 4 or 5, negative 1 or 2 stands for extreme, 3 stands for neutral</td>
</tr>
<tr>
<td>Affection</td>
<td>Dependent</td>
<td>The affect score from LIWC for the body of the review, capturing mentions of emotional keywords.</td>
</tr>
<tr>
<td>Adverb</td>
<td>Dependent</td>
<td>The adverb score from LIWC for the body of the review, capturing mentions of emotional keywords.</td>
</tr>
<tr>
<td>Valence</td>
<td>Dependent</td>
<td>A positive integer value between 1 and 5 representing the star rating of the review.</td>
</tr>
<tr>
<td>No. of Fans</td>
<td>Dependent</td>
<td>The number of followers of each reviewer</td>
</tr>
<tr>
<td>Price</td>
<td>Dependent</td>
<td>The average price of the certain consumption</td>
</tr>
<tr>
<td>Readership</td>
<td>Dependent</td>
<td>Number of hit the review received</td>
</tr>
</tbody>
</table>
Table 3. Comparative Study Statistics of Study One

<table>
<thead>
<tr>
<th>Variable</th>
<th>Population</th>
<th>Mobile</th>
<th>Desktop</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St.Dev.</td>
<td>Min</td>
</tr>
<tr>
<td>Portal</td>
<td>0.71</td>
<td>0.45</td>
<td>0.00</td>
</tr>
<tr>
<td>Length</td>
<td>47.89</td>
<td>67.56</td>
<td>12</td>
</tr>
<tr>
<td>Extremity</td>
<td>0.85</td>
<td>0.36</td>
<td>0.00</td>
</tr>
<tr>
<td>Affection</td>
<td>0.73</td>
<td>4.26</td>
<td>0.00</td>
</tr>
<tr>
<td>Adverb</td>
<td>0.71</td>
<td>4.57</td>
<td>0.00</td>
</tr>
<tr>
<td>Followers</td>
<td>9.74</td>
<td>407.49</td>
<td>0.00</td>
</tr>
<tr>
<td>Price</td>
<td>79.43</td>
<td>337.4</td>
<td>0.00</td>
</tr>
<tr>
<td>Readership</td>
<td>1,497</td>
<td>3,080</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Notes: Population=1,048,575; Mobile=744,488; Desktop=304,086

We then employ the two-way fix effect mode with time specific dummy (Cornelissen 2009). Equations 1 below, clarify our econometric specification. The fixed effect assumption is that the individual specific effect is correlated with the independent variables. We index reviewers by $i$, restaurants by $j$, and month by $t$. These controls respectively address unobserved heterogeneity across reviewers (e.g., personal characteristics or persistent preferences), business (number of branches), and time (e.g., temporal trends in reviewing behavior or unobserved).

All of our other DVs are estimated using a specification of the form depicted in Equation. We focus on the mobile effect but beyond these outcome measures, we also incorporate a number of controls. Most notably, we include fixed effects for reviewers, restaurants and time (month) in all of our estimations.

$$y_{ij} = \beta_i * portal_{ij} + \lambda_i + \phi_j + \delta_t + \varepsilon_{ijt}$$
3.1.5.4 The Results

The primary regression results for each of our hypothesis tests in Table 4. Each row in the table reflects a separate regression with a different dependent variable, evaluating a different hypothesis. Row one pertains to Hypothesis 1, regarding review length. As noted previously, we hypothesized that all else being equal, mobile reviews are expected to be shorter in length, primarily because the greater physical and cognitive costs associated with using mobile devices when on the move. The differences in review content is derived directly from the nature of the medium (in this case, a limited user interface). The second row provides results that pertain to Hypothesis 2, of the extremity. We find that mobile reviews are more extreme. In particular, we observe that, mobile reviews contain more absolute positive and negative ratings than the neutral ones. Supporting the idea that greater availability increases the likelihood of more extreme ratings from mobile WOM, consistent with our hypotheses and predictions. Row three demonstrates the effect of mobile device usage on the probability that review text contains keyword indications of emotion (Hypothesis 3). As hypothesized, we observe that mobile reviews are significantly more likely to contain text of this sort. Row four shows the positivity of the mobile reviews. In line with the idea that the real-time creation process associated with mobile WOM reduces retrospective biases, the result shows that mobile ratings are more positive than the desktop ones. The rest of three rows indicate the external usage conditions of m-WOM, which is “use by whom”, “on what products” and “how popular”. The results reveal
that those mobile reviewers have less number of fans and mainly talking on less pricy consumption, which all taking together, make them less read because its commonality.

Table 4. Mobile WOM Attributions

<table>
<thead>
<tr>
<th>Fix Effect Model</th>
<th>Mobile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependents Variables</td>
<td></td>
</tr>
<tr>
<td>Length (/100)</td>
<td>-0.912***</td>
</tr>
<tr>
<td>Extremity</td>
<td>0.280***</td>
</tr>
<tr>
<td>Affection</td>
<td>0.022***</td>
</tr>
<tr>
<td>Adverb</td>
<td>0.213***</td>
</tr>
<tr>
<td>Valence</td>
<td>0.532***</td>
</tr>
<tr>
<td>No. of Followers</td>
<td>-0.024***</td>
</tr>
<tr>
<td>Price</td>
<td>-0.004***</td>
</tr>
<tr>
<td>Readership (/1000)</td>
<td>-0.536***</td>
</tr>
</tbody>
</table>

Notes: *** p < 0.001, ** p < 0.01, * p < 0.05;

3.1.6 Conclusions

Different from in the past, mobile devices are the new driver of WOM that disseminate information to consumers. With the increasing change of user behavior, this first study aims to verify the basic characteristics of m-WOM when compared with the desktop ones.

The results of this study support our hypotheses that m-WOM has its own distinctive features when compared with the d-WOM. In brief, m-WOM is shorter, more emotional and more extreme. It comes from common consumers with less followers who would like to express their own strong satisfaction or dissatisfaction right after or even during the consumption, rather than pose a professional critic. Moreover, m-WOM is mostly related less expensive products instead of the expensive ones.

We predict that some aspects of mobile WOM should increase its value while other
aspects should decrease it. Hence, we will further study how these distinctive attributes affect the readers’ perception of m-WOM in terms of helpfulness and credibility and how they influence the ultimate purchase and consumption decisions.
3.2 Study Two: The Value of m-WOM in Terms of Its Helpfulness

3.2.1 Introduction

Ubiquitous mobile devices allow users to engage in activities in diverse physical locations, to access resources specific to the time, and to communicate directly or indirectly with others. The integration of those resources can potentially affect people’s perceptions and judgments within a particular context.

Compared with the traditional WOM, consumers can respond to the environmental stimuli immediately by using mobile devices, rather than post the photos and articles after going back to a PC or a laptop. The disappearance of constraint related to time and space provides flexibility to consumers to share information. As per our findings in study one, there are several unique characteristics of m-WOM that are due to the mobile device’s features: size, mobility, closeness to the users.

With the the development of mobile device functions, wireless Internet, and SNS, the WOM’s effectiveness is also evolving. The psychological distance affects the WOM perception, including temporal, spatial and social distances. WOM readers often have action goals such as “Which product should I choose now?”. WOM that reflects a more concrete (vs. abstract) construal level, where feasibility concerns such as “Where is the closest place to eat?” dominate desirability concerns such as “Which is the best restaurant?”. The same effect also influences the senders (WOM generators). WOM generated right after the consumption reflects a lower construal level than desktop.
WOM since the temporal and spatial contiguity, as shown by a greater focus on current (rather than a distant past) concerns (Trope and Liberman 2010; Trope and Liberman 2003). Work on temporal construal has traditionally examined the mental representation of future events, however, more recent research suggests that effects of psychological distance apply in similar ways to retrospective evaluations (Trope and Liberman 2010). Since the mobile technology draws us more attached to the device, we are interested in the helpfulness of WOM by using smartphone in our second study. We first present a literature review of both WOM effectiveness in terms of the product type and psychological distance, then discuss the Construal Level Theory and its implications in mobile context. We develop a theoretical framework based on past studies and test our propositions by analyzing the data from Dianping.com. Finally, we discuss the implications of findings and for the rationale for the next study regarding the effect of m-WOM on purchase activities.

3.2.2 Literature Review

This study concentrates on the m-WOM’s helpfulness, it is based on theoretical insight from construal level to the perception of WOM on the mobile device. Therefore, we start with the review of studies of the WOM and its helpfulness, follow with the introduction of the psychological distance research and their implications for the study of mobile WOM.

3.2.2.1 WOM’s Helpfulness

Research on helping behavior provides a pertinent foundation in investigating WOM
helpfulness in the context of online shopping. With limited time and resources, consumers look for relevant information from a large volume of information to alleviate purchase uncertainty (M Li et al. 2013). WOM from customers or experts provides potential buyers relevant information on the usage experience and product features of the target product; such knowledge facilitates the purchase decision process. When consumers read product reviews from the Internet, they perceive the product review as an endorsement of the reviewers’ desire to help, commitment, and reciprocity for facilitating other consumers’ purchase decisions (M Li et al. 2013). Therefore, WOM’s helpfulness is a formative construct consisting of three dimensions: (1) credibility, (2) diagnosticity, and (3) vicarious expression. The theoretical foundation of this definition comes from Bach’s (1967) research on helping behavior, in which helpfulness has three dimensions: (1) trustworthy (2) problem-solving, and (3) insight mediation.

Online retailers have commonly used review “helpfulness” or “Like” as the primary way of measuring how consumers evaluate a WOM. They can be seen as a reflection of review’s quality. Interpreting helpfulness as a measure of perceived value in the decision-making process is consistent with the notion of information diagnosticity (Jiang and Benbasat 2004; Kempf and Smith 1998; Pavlou and Fygenson 2006). It can provide diagnostic value across multiple stages of the purchase decision process, including need recognition, information search, evaluation of alternatives, purchase decision, purchase, and post-purchase evaluation. The ability to explore information
about alternatives helps consumers make better decisions and experience greater satisfaction with the online channel (Kohli et al. 2004). This implies that helpful reviews offer greater potential value to customers.

Furthermore, two features of WOM, the source (e.g., authorship of product reviews) and content (e.g., content abstractness) features, are also the important criteria of WOM’s helpfulness. These complement the questions, i.e., “Who says what?” and “what he says”. Scholars have argued that source and content are two important perspectives when assessing the impact of information. De Bono and Harnish (1988) investigated the impact of authorship and the quality of content argument on the persuasiveness of counter attitudinal message. Borgida and Nisbett (1977) argued that the concreteness of information is a critical factor for decision behavior. Specifically, Forman and colleagues (2008) observed that the product reviews’ source identity-descriptive information (e.g., authorship of the product reviews) can be used to supplement or replace the product information when consumers evaluate the product or service. Other scholars, in a similar vein, discover a high correlation between the disclosure of the authorship of the product reviews and the consumers’ evaluation of the reviews’ helpfulness. For instance, one study finds that consumers perceive product reviews as diagnostic, only when the reviews transmit clear information. Another study discovers that the length of review content could significantly influence the perceived diagnosticity of product reviews (Schindler and Bickart 2012).
3.2.2.2 Psychological Distance

Psychological distance is a subjective experience that something is close or far away from the self, here, and now. Psychological distance is thus egocentric: Its reference point is the self, here and now, and the different ways in which an object might be removed from that point. Time, space, social distance, and hypotheticality constitutes different distance dimensions. Although many studies have documented the effectiveness of online WOM (Godes and Mayzlin 2004; Tirunillai and Tellis 2012), only recently has research begun to examine the psychological processes underlying the creation and evaluation of WOM (Berger and Schwartz 2010; Cheema and Kaikati 2010; Wojnicki and Godes 2013).

Social Distance

The effects of social influence in the network environment offer strong theoretical footing for examining the effect of online product reviews on the latecomer’s purchase behavior and sales of products. Social influence occurs when one's emotions, opinions, or behaviors are affected by others (Kelman 1958). Social influence effects on online product ratings are substantially large (Sridhar and Srinivasan 2012). It suggests that people combine their ideas and the opinions of others in their decision making. Iyengar and Valente (2011) studied how opinion leadership and social contagion within social networks affect the adoption of a new product. Huang and Chen (2006) conducted three studies examining herding in product choices on the Internet. Their experimental results revealed that subjects used the choices and evaluations of others as cues for
making their own choices.

People experience conformity pressures from other members within a social group. The actions of others have a powerful effect on a given member's behavior and the influence of conformity is varied across the social distance (Cialdini and Goldstein 2004). The theory on social distance not only differentiates between the self and others, but also between close others (e.g., in-groups or similar others) and distant others (i.e., out-groups or dissimilar others) (Trope et al. 2007). Intuitively, one would expect that, when making a recommendation, close others would always be more effective than distant others. A related finding in a previous study (Duhan et al. 1997) supports this assumption: consumers are more likely to use recommendation sources that have close relationships to them than those that are more distant.

Temporal Distance

Temporal distance, the degree to which events are close or distant to each other in time, is the dominant perceptual cue humans use to establish causality between physical events (Bullock, Gelman, and Baillargeon 1982; Heider and Simmel 1944; Michotte 1963). In the absence of that, perception of causality is greatly impaired (Buehner and May 2003; Shanks, Pearson, and Dickinson 1989). Studies of temporal construal have concentrated on causal attributions for physical events. However, more recent research suggests the idea that temporal closeness/contiguity matters when making causal inferences about human behavior and effects of psychological distance apply in similar ways to retrospective evaluations. Kelley (1973) proposed a model of attribution based
on the assumption that "a close temporal relation is essential to a causal interpretation" and that "effects are ordinarily assumed to occur closely after their causes." In the same vain, the awareness of a closer temporal distance will connect the product experience to the review and therefore facilitating perceptions that the mobile review which is generated right after the consumption is driven by the product experience rather than the reviewer’s biased recall, which makes it more credible and helpful.

3.2.2.3 Product Type

Although the consumption of many goods involves both dimensions to varying degrees (Batra and Abtola 1991), it is found that consumers characterize some products as primarily hedonic and others as primarily utilitarian. We define hedonic goods as ones whose consumption is primarily characterized by an affective and sensory experience of aesthetic or sensual pleasure, fantasy, and fun (Hirschman and Holbrook 1982). Utilitarian goods are ones whose consumption is more cognitively driven, “useful, practical, functional, something that helps you achieve a goal” (Strahilevitz and Myers 1998).

This section of the literature review outlines a number of distinctions between hedonism and utilitarianism that have been identified and their relationship with WOM effectiveness. Hedonic consumption provides the consumer with intangible affective benefits such as excitement and fun. On the other hand, utilitarian consumption provides the consumer with functional and more task-related benefits such as usefulness and practicality (Babin, et al. 1994; Chaudhuri 2002; Chernev 2004).
It is suggested in the literature that hedonic and utilitarian values are both discretionary in the sense that both depend on the consumer’s perception (Okada 2005). Nevertheless, this notion is also followed by the argument that the hedonic value is more discretionary than its utilitarian counterpart (Khan, Dhar, and Wertenbroch 2004). This is because hedonic consumption tends to be more personal and subjective than utilitarian consumption. Therefore, feelings play a significant role in hedonic consumption. On the other hand, because utilitarian consumption focuses on instrumental benefits, objective calculation of the benefits tends to assume greater importance.

In terms of the evaluation, it has been proposed in the literature that hedonic consumption requires emotional evaluation, whereas utilitarian consumption requires rational evaluation (Arnold and Reynolds 2009; Chaudhuri 2006). Since hedonic benefits are experiential, they are difficult to quantify. Therefore, in order for such benefits to be evaluated, the consumption experience must be accompanied by a state of emotional arousal or intense affection. In contrast, because utilitarian benefits are instrumental, evaluation of such benefits is akin to a calculative process. Hence, there is an interaction between product type and WOM content, as different products vary in their information needs.

Hence, besides the previous discussion of WOM content and reviewers, we integrate psychological distance and product/service type to assess the influence of the m-WOM’s value and helpfulness. Mobile devices, including their sensors, applications
and other distinguished features, greatly affect the helpfulness of reviews, which vary across product categories.

3.2.3 Theoretical Background

Mobile devices are linked to the physical body and follow us around, they are egocentric, in that they are tied to a person, rather than to a physical location. Because of this attachment, they can directly influence the user during a behavioral decision (Larson and Csikszentmihalyi 1983). Here, we argue that the primary concept associated with this egocentric character is the construal level theory, including three dimensions of psychological distance—spatial location, time, and social proximity (Chen, Hekler, Hu, Li, and Zhao 2011).

Construal level theory has emerged as a “leading contemporary theory” in the fields of social psychology and consumer behavior. However, this theoretical perspective has not yet been widely applied to the study of media psychology and studies of mobile devices. It refers to the degree of abstraction at which events, objects, or people are represented in the cognitive hierarchy. High-level construals are general, relatively abstract, and schematic, decontextualized, and superordinate mental representations, while low level construals are specific, detailed, concrete, unstructured, contextualized, subordinate mental representations (Trope and Liberman 2010). It holds that we tend to think about close items more concretely and far items more abstractly (Trope and Liberman 2010). The central premise is that increased distance enhances the abstractness and level of mental construal of an event. It informs how message creators
can effectively construct and deliver persuasive messages and how receivers will successfully process messages.

According to Cesario, Grant, and Higgins (2004), matching the content of a message to some aspect of the message recipient’s cognitive, motivational, or affective system can enhance effectiveness. Because psychologically near events tend to be represented concretely and psychologically distant events tend to be represented abstractly, therefore, the information processing is more efficient when there is a congruency between the portrayed distance and the presentation medium (Amit 2009). Matching psychological distances enhances effectiveness and confers value from fit (Higgins 2000). In this study, we integrate research on temporal and social distances and draw on the “fit” literature to predict that when consumers receive other people’s recommendations, they are perceived to be effective when these dimensions are congruent.

Thus, it is anticipated that matching the construal level with type of appeal can increase helpfulness of WOM. Specifically, appeals emphasizing product benefits will be more effective when psychological distance is high or when paired with a higher level, abstract mind-set, whereas appeals emphasizing product attributes will be more effective when psychological distance is low or when paired with a lower-level, concrete mindset.

3.2.4 The Conceptual Model

Different factors may affect consumers’ responses to others’ recommendations. In this
study, we focus on the psychological distance, product type and medium effect. To be specific, our conceptual model studies to what extent consumers value these recommendations as a result of the match of the construal levels and consumption type and whether this effect is amplified by using mobile device.

Concerning social distance, out-group/association member’s behavior or opinion (e.g., other people’s recommendations about a product) is construed as more abstract than those from one’s own within-group (Trope et al. 2007). When doing WOM browsing, consumers often have lower construal level action goals such as “what are people saying about it? Therefore “My friend’s recommendations/opinions” which represent a closer social construal are paid more attention than those unrelated strangers. We hypothesis that:

**H8: WOM from an associated group is perceived more helpful than that from a non-associated group.**

Concerning temporal distance, recent opinions (e.g., WOM which is just generated) are construed as lower and concrete than the ones which posted long time ago. Consumers seek for the knowledge of “what’s the latest news.” Therefore, the new posts of recommendations and opinions will be paid more attention and considered more helpful than those past old ones. Thus, we hypothesis that:

**H9: WOM is perceived more helpful when it is temporally closer to the focal readers than when it is farther.**

Mobile devices are tied closely to their users. Unlike desktop computers, they are often
used to seek for the instant answers of “right now, right here and myself”. By using the mobile device, individual’s mental construal is drawn to a lower level in that they are more likely to find their decisions influenced by context and environmental specific factors. Applying this to the dimensions of psychological distance, we hypothesize that the construal level theory is more saliently reflected by using mobile device.

**H10: The effect of lower construal levels on the WOM helpfulness is amplified by mobile devices.**

Further, the literature suggests an interaction between product type and review helpfulness: hedonic products are more subject to the influence of the product attributes as well as the volume of the reviews, which signals the popularity of a product (Cui, Lui, and Guo 2012), while utilitarian goods are more affected by the product benefits with textual descriptions that can be better digested and comprehended before a decision making. Review length increases the diagnosticity of a utilitarian goods review more than that of a hedonic good review. Reviews of utilitarian goods lend themselves more easily to a textual description than do reviews of hedonic goods (Mudambi et al. 2010).

In study one, we already find that desktop reviews are averagely longer (in terms of the word count) but carrying less affective contents than the m-reviews. Likewise, we hypothesize that there is an interplay between product type and WOM medium, that:

**H11a: Mobile-WOM is perceived more helpful for hedonic products than for**
utilitarian products.

**H11b: Desktop-WOM is perceived more helpful for utilitarian products than for hedonic products.**

### 3.2.5 Empirical Analysis

#### 3.2.5.1 Data Description

The study examines and compares the effect of WOM from desktop and mobile on consumers by incorporating the contextual variables of product category and temporal and social distances. By using the same set of secondary data collected from Dianping.com, we study the helpfulness of reviews and its interplay with product types and the construal levels.

The data we used in this study are the same as those in study one. We randomly collected the review data for 6270 businesses (including branches), covering dining, and car caring service, from Jan 1 to Dec 31 2014, including both desktop and mobile portals. For each review, we extracted the business information; review text and rating and reviewers’ social networks. Most importantly, we collected the number of people who found the review to be helpful.

<table>
<thead>
<tr>
<th>Item</th>
<th>Amount</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of Reviews</td>
<td>1,048,575</td>
<td>Total Sample</td>
</tr>
<tr>
<td>Rank of Readership</td>
<td>0-191,322</td>
<td>Readership</td>
</tr>
<tr>
<td>Rank of Review Length</td>
<td>2-345</td>
<td>Word Counts</td>
</tr>
<tr>
<td>Rank of Helpfulness</td>
<td>0-152</td>
<td>Vote for helpfulness</td>
</tr>
<tr>
<td>Rank of Temporal Interval</td>
<td>0-314</td>
<td>Temporal distance (hours)</td>
</tr>
<tr>
<td>Type of Relationship</td>
<td>4</td>
<td>Relationship between voter and reviewer</td>
</tr>
</tbody>
</table>
3.2.5.2 Methodology

We used Tobit regression to analyze the model, the reason to use Tobit is the censored nature of our data and potential selection bias inherent in this type of sample. According to Kennedy (1994), if the probability of being included in the sample is correlated with an explanatory variable, the OLS and GLS estimates can be biased. There are several reasons to believe these correlations may exist. First, people may be more inclined to vote on extreme reviews, since these are more likely to generate an opinion from the reader. Following similar reasoning, people may also be more likely to vote on reviews that are longer because the additional content has more potential to generate a reaction from the reader. Even the number of votes may be correlated with likelihood to vote due to a “herding” effect. Therefore, we used Tobit regression to analyze the data.

The dependent variable is helpfulness. we operationalized it as the number of "helpful" votes a review received from other users. The explanatory variables are WOM attributes including rating, review length, readership, time (the time span between the time when the review is generated and the time when it receives a helpfulness vote), emotional sentiment (density of affection and adverb); business attributes including average price, product type, and number of branches. Since the hedonic goods are the ones whose consumption is primarily characterized by an affective and sensory experience of aesthetic or sensual pleasure, fantasy, and fun. Utilitarian goods are ones whose consumption is more cognitively driven, instrumental, and goal oriented and
accomplishes a functional or practical task (Strahilevitz and Myers 1998). As such, the dining is categorized as hedonic consumption while car care is classified as utilitarian. Reviewer attributes including their social relationship with each voter and number of fans they have. Social distance is defined as the bidirectional, unidirectional and unassociated (out-group) relationships between the reviewers and the readers for each review. Like Yelp, Dianping.com offers its users the social function. But this social relationship is largely based on the shared taste or appreciation of the quality between reviewers and readers, rather than the real acquaintances in other social network sites such as Facebook. Users may choose the ones they want to follow depending how good they are in picking the restaurant and writing a review. The data indicates the relationship between a voter and reviewer in four groups, namely, type zero: no relationship, means neither party is related; type one: the one who votes the review to be helpful is a fan of the one who wrote the review; type two: the one who votes the review to be helpful is a be followed of the one who wrote the review and lastly, type three: two parties are mutually following each other.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Helpfulness</td>
<td>Dependent</td>
<td>A positive integer value representing the number of times the review has been voted as helpful by other Dianping users.</td>
</tr>
</tbody>
</table>

**Table 6: Variable Definitions of Study Two**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portal</td>
<td>Independent</td>
<td>A binary indicator of whether the review was entered via a mobile device.</td>
</tr>
<tr>
<td>Length</td>
<td>Independent</td>
<td>A positive integer value representing the number of characters in the body of the review.</td>
</tr>
</tbody>
</table>
We first compare the variables from two portals especially on their temporal (leading time for voting); social factors, and product type (hedonic and utilitarian). The result is unsurprising and intuitive according to the previous findings of the m-WOM’s
characters: m-WOM is voted less helpful (0.20 vs 0.44); the average leading time it takes to vote an m-WOM is 2.64 hours while the same interval to desktop ones is 27.35 hours and the helpfulness votes vary in terms of the review portal and social relations, the closest type of relations (mutual-friend) gains more votes on m-WOM (0.10 vs 0.07). As to the consumption type, the result also indicates that m-WOM is voted more helpful for hedonic consumption while the utilitarian products receive most votes of helpfulness from the desktop portal.

Table 7: Comparative Statistics of Study Two

<table>
<thead>
<tr>
<th>Variable</th>
<th>Population</th>
<th>Mobile</th>
<th>Desktop</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St.Dev.</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>Helpfulness</td>
<td>0.27</td>
<td>1.27</td>
<td>0.00</td>
<td>152.00</td>
</tr>
<tr>
<td>Temporal Distance</td>
<td>9.80</td>
<td>35.60</td>
<td>0.00</td>
<td>959.00</td>
</tr>
<tr>
<td>Type Zero</td>
<td>0.10</td>
<td>0.39</td>
<td>12.00</td>
<td>23.00</td>
</tr>
<tr>
<td>Type One</td>
<td>0.07</td>
<td>0.72</td>
<td>0.00</td>
<td>120.00</td>
</tr>
<tr>
<td>Type Two</td>
<td>0.01</td>
<td>0.10</td>
<td>0.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Type Three</td>
<td>0.09</td>
<td>0.64</td>
<td>0.00</td>
<td>52.00</td>
</tr>
<tr>
<td>Product Type</td>
<td>0.97</td>
<td>0.17</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Hedonic</td>
<td>0.28</td>
<td>1.27</td>
<td>0.00</td>
<td>152.00</td>
</tr>
<tr>
<td>Utilitarian</td>
<td>0.18</td>
<td>1.12</td>
<td>0.00</td>
<td>60.00</td>
</tr>
<tr>
<td>Branch</td>
<td>2.38</td>
<td>5.78</td>
<td>0</td>
<td>125</td>
</tr>
</tbody>
</table>

Notes: Population=1,048,575; Mobile=744,488; Desktop=304,086

In H8 and H9, we hypothesized that WOM is consider to be more helpful if it is socially closer to the reader and temporally closer to the consumption, hence, in Model 1 we use the temporal and social variables as our explanatory parameters and use the rest of other variables including review attributes, reviewer attributes and business attributes as our control variables. In Model 2 and 3, we compare the portal effect by using the two separated data, namely, mobile and desktop, to test whether the construal
level effect is manifested during the mobile usage. Lastly, we expect that there will be an interplay between product type and review portal in terms of WOM helpfulness, we include an interaction term in the Model 4. The resulting model is

\[ y_i^* = x_i \beta + \epsilon_i \]

\[ y_i^* = \begin{cases} y_i^* & \text{if } y > 0 \\ 0 & \text{if } y \leq 0 \end{cases} \]

Helpfulness\_population = \beta_1 \text{Portal} + \beta_2 \text{Temporal Interval} + \beta_3 \text{Social Relationship} + \beta_4 \text{Review attributes} + \beta_5 \text{Reviewer attributes} + \beta_6 \text{Business attributes} + \epsilon \quad (1)

Helpfulness\_desktop = \beta_1 \text{Temporal Interval} + \beta_2 \text{Social Relationship} + \beta_3 \text{Review attributes} + \beta_4 \text{Reviewer attributes} + \beta_5 \text{Business attributes} + \epsilon \quad (2)

Helpfulness\_mobile = \beta_1 \text{Temporal Interval} + \beta_2 \text{Social Relationship} + \beta_3 \text{Review attributes} + \beta_4 \text{Reviewer attributes} + \beta_5 \text{Business attributes} + \epsilon \quad (3)

Helpfulness\_population = \beta_1 \text{Temporal Interval} + \beta_2 \text{Social Relationship} + \beta_3 \text{Review attributes} + \beta_4 \text{Reviewer attributes} + \beta_5 \text{Business attributes} + \beta_6 \text{Product type} + \beta_7 \text{Product type} \times \text{portal} \quad (4)

### 3.2.5.3 Analytical Results

The current study is interested in whether construal level matters in the perceived helpfulness and whether these effects will be amplified by WOM and portal. Construal level theory has the potential to impact how we effectively deliver and perceive messages. Here, we posit that mobile device works as an extension of ourselves, it will further narrower the psychological distance and the amplifier the construal level effects. m-WOM will play a significant role when it is socially or temporally matched with the contextual need.

Table 8 shows the results of the effect of the mobile platform and WOM content on...
Review helpfulness. Model 1 includes the whole population; Model 2 is the desktop review result; Model 3 examines the mobile portal; and Model 4 includes the fixed effects for product types. We find that the mobile platform leads to WOM content that has both positive and negative effects on WOM helpfulness. This makes it difficult to predict a-priori when and how mobile WOM will be more or less valuable than desktop WOM. Our empirical analysis finds, across a variety of specifications, that although mobile WOM is perceived less helpful in general, but the construal level is drawn lower by using mobile device. Model 1 includes portal dummy and finds that m-WOM gets lower chance of being voted for helpful ($\beta = -.78$) and supports our hypotheses that WOMs are perceived to be more helpful if they are temporally and socially more close to the receivers. When consumers are on the move and seeking for consumption related information with smartphone or other portable devices, they hardly can have a steady environment for comprehensive research. Instead, they want the most updated and reviews that are just released, concerning the present situation including the service and goods quality. The presence of temporal and social contiguity enhances of the value of the reviews of the consumption experience, facilitating perceptions of trustworthiness in that the review is driven by the true product experience.

The comparison result of Model 2 and 3 clearly confirms the interactive effects of both portal and construal levels. We find salient portal amplification effect in that both social and temporal distance is drawn closer when vote for the helpfulness of m-WOM,
which in our interpretation is, the degree of WOM acquaintance to the reviewer is more weighted in evaluating the helpfulness. Model 4 includes the product type. We find that m-WOM of hedonic consumption is perceived to be more helpful while its value on the utilitarian goods is weighted the lowest, Thus, there is significant interaction effect between product type and review portal. Therefore, hypothesis 11 is supported.

Table 8: Value of m-WOM (Tobit Model)

<table>
<thead>
<tr>
<th>Dependent Variable: Helpfulness</th>
<th>Model 1 (population)</th>
<th>Model 2 (desktop)</th>
<th>Model 3 (mobile)</th>
<th>Model 4 (population)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Portal</td>
<td>-0.78**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>WOM attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Length/(100)</td>
<td>0.32**</td>
<td>0.54**</td>
<td>0.27**</td>
<td>0.33**</td>
</tr>
<tr>
<td>Valence</td>
<td>0.73*</td>
<td>0.46*</td>
<td>0.81*</td>
<td>0.73*</td>
</tr>
<tr>
<td>Affection</td>
<td>-0.003</td>
<td>0.002</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Adverb</td>
<td>0.002*</td>
<td>-0.002*</td>
<td>-0.003*</td>
<td>-0.002*</td>
</tr>
<tr>
<td>Readership/(1000)</td>
<td>0.029**</td>
<td>0.029**</td>
<td>0.032**</td>
<td>0.031**</td>
</tr>
<tr>
<td>Extremity</td>
<td>-0.162</td>
<td>0.290**</td>
<td>0.217**</td>
<td>0.217**</td>
</tr>
<tr>
<td>Temporal Interval</td>
<td>0.21*</td>
<td>0.014**</td>
<td>0.53**</td>
<td>0.147**</td>
</tr>
<tr>
<td>Social relationship</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Type Zero</td>
<td>1.58**</td>
<td>0.413**</td>
<td>0.27**</td>
<td>0.31**</td>
</tr>
<tr>
<td>Type One</td>
<td>0.566**</td>
<td>0.644**</td>
<td>0.47*</td>
<td>0.51**</td>
</tr>
<tr>
<td>Type Two</td>
<td>0.081</td>
<td>0.08</td>
<td>0.073</td>
<td>0.08</td>
</tr>
<tr>
<td>Type Three</td>
<td>1.48**</td>
<td>0.317**</td>
<td>0.679**</td>
<td>0.51**</td>
</tr>
<tr>
<td>Business Attributes</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product type</td>
<td>0.74**</td>
<td>-0.56**</td>
<td>0.39**</td>
<td>0.71**</td>
</tr>
<tr>
<td>Branches</td>
<td>0.051</td>
<td>0.037</td>
<td>0.067</td>
<td>0.049</td>
</tr>
<tr>
<td>Price</td>
<td>0.013</td>
<td>0.54*</td>
<td>-0.086*</td>
<td>0.159*</td>
</tr>
<tr>
<td>Interaction</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product type x portal</td>
<td>-0.46*</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Observation: 1,048,573  *** p < 0.001, ** p < 0.01, * p < 0.05

3.2.6 Conclusions

This study introduces the construal level theory and extend it to the mobile content,
integrating previous research and articulating several propositions. Taken together, our findings show that WOM is more helpful when it is socially closer to the receiver and temporally closer to the consumption, and this effect is amplified on m-WOM. Thus, when the natural mental construal associated with other people’s opinions is congruent, both of which take place at a low level, consumers perceive these recommendations and reviews to be more relevant in this circumstance. Further, we show that consumers also perceive review’s helpfulness differently depending on the interaction between product type and the portal it is generated. In other words, product type partly moderates the influence of review portal on perceived review helpfulness. Specifically, m-WOM is perceived valued more for hedonic consumption and least valued for utilitarian ones.

This study integrates different dimensions of psychological distance and find the congruency of construal levels between social distance and temporal distance leads to greater impact of WOM through the mobile device. We believe that these findings have meaningful implications. For designers of online review platforms, they may leverage the impact of reviews through the lens of our research findings. To improve the impacts of systematic processing, the platform should be careful in monitoring the content of reviews contributed by users, portal and context. Low levels of informative and persuasive reviews can be presented to the hedonic consumption such as restaurants and the high levels of holistic information can be more shown on the utilitarian products.
In the following study, we will uplift the investigation into the next level: how these distinctive attributes and readers’ perception may ultimately lead to consumption and show how m-WOM compares with the ones from fixed portal in conversion and revenue generation.
Study Three: The Effect of m-WOM on Deal Purchase

3.3.1 Introduction

In the retail sphere, smartphones have become the key tools for browsing, searching and comparing. With the wide adoption of mobile devices, companies are increasingly using mobile marketing tactics to reach consumers and promote their products. The mobile channel or ‘m-commerce’ represents a huge opportunity for retailers, especially for impulsive purchases. The on-the-move browsing, evaluation, real-time deal offering, make it easy and convenient, for consumers to receive promotional deals and make purchases.

As a result, spending on short-term incentives designed to trigger those impulsive purchases (e.g., coupons, rebates, price-off deals) has grown dramatically in recent years. Business owners are increasingly using these for promoting a new product and stimulating the sales. These promotion deals are often listed on platforms such as Groupon and Dianping. Both the popularity and reviews of a deal are displayed on the same page on the website to show how other consumers evaluate the offers. Marketers can further enhance impulsive reactions by providing potential consumers real-time information of the deal, including accumulative sales and deal reviews.

Past research suggests that consumer purchase decisions result from some combination of cognitive and affective processes. The “dumb down” price promotion deal aims at increasing sales by lowering its original price, reducing cognitive processing and, allowing affect or feelings to play a greater role in choice behavior. Specifically, they
argue that price cut lowers a consumer's motivation to exert mental effort so that purchase decisions are guided less by extensive information processing but triggered by faster and perhaps stronger affective responses (Aydinli, Bertini, and Lambrecht 2014).

In the first two studies, we have identified several distinctive characteristics of m-WOM, particularly the stronger affective sentiment in m-WOMs. We also found that the effect of lower construal level or closer psychological distance is amplified by using mobile devices and such effect differs depending on the type of product. In the third study, we examine how m-WOM and d-WOM influence the adoption and purchase of promotion deals.

Here, we draw from the research on observational learning and social influence. Prior studies have documented that popularity and social influence affect consumer behaviors (Zhang 2010; Zhang and Liu 2012). We extend the study of social influence in the mobile setting in four ways: (1) the impact of herding, and how observational learning and social influence affect promotion adoption in mobile context; (2) the effect of m-WOM on consumer purchases; (3) compare and contrast such of this effect with that from the desktop reviews.

The rest of this chapter is organized as follows. In next section, we review the relevant literature and present a theoretical framework on how m-WOM influences consumers’ impulsive buying behavior and planned consumption behavior. Next we report the results of data analysis, to be followed by the discussion of the implications based on
our findings and the directions for future research.

3.3.2 Literature Review

Recently, researchers have examined how the time and location congruency affect consumer behavior and how the use of mobile devices influence consumption related activities. For instance, Luo and Seyedian (2003) conducted an empirical analysis of contextual marketing and find that both timing and location affect consumer purchases on the mobile platform. Luo, Gu Fang, and Xu (2013) attempted to quantify the dynamic sales impact of location-based mobile promotions. Molitor, Reichhart, and Spann (2012), and Ghose (2013) examined the effectiveness of location-based advertising using a randomized field experiment. They find that the effectiveness of targeting consumers when the time and distance congruency is present. In the third study, we examine how the real-time WOM influences the effectiveness of price promotions and consumption behavior. In this section of literature review, we discuss the related studies of both mobile promotion and the effectiveness WOM in affecting of deal purchase.

3.3.2.1 Mobile Promotion

Mobile technology has a number of unique characteristics compared with traditional information and communication technology. The unique characteristics of mobile technology include its higher accessibility (Nysveen et al. 2005; Ghose, Hann, and Goldfarb 2012), which makes mobile promotion an ideal channel for real-time marketing.
Prior literature affirms that the timing of promotions impacts their effectiveness (Zhan and Krishnamurthi 2004). For example, Prins and Verhoef (2007) show how marketing communications reduce consumers’ adoption time for a new mobile e-service. Acquiring real-time insight into customer needs help companies developing competitive advantages when they adopt a “speed versus sloth” approach. Indeed, the timely interactions enabled by mobile technologies allow marketers and customers to maintain continuous connections that foster the transition from real-time insight to real-time action.

3.3.2.2 Impulsive Buying

Impulsive buying and real-time (contemporaneous) purchases refer to consumers’ experience of “a sudden and unplanned urge that is immediately gratifying or acting on an impulse without careful deliberation of the negative or long-term consequences” (Mishra and Mishra 2010; Sengupta and Zhou 2007). This definition suggests two key elements in the activation of impulsive buying: (1) emotions and feelings play a decisive role in purchasing, triggered by seeing the product or upon exposure to a well crafted promotional message, and (2) the psychological state that allows the desire to instantly fulfill the consumption needs to overweigh various inhibiting factors. Physical proximity, temporal proximity, and social comparison together may reduce the effect of inhibiting factors and lead to impulsive buying (Hoch and Loewenstein 1991). When a user is close to the consumption object both physically and temporally, the denial of consumption would cause a sense of psychological deprivation. This
deprivation increases desire and impatience, and consequently stimulates purchase behavior (Ainslie 1975; Loewenstein 1988).

3.3.2.3 WOM and Promotion

In the price promotion setting, consumers may find it difficult to ascertain a deal’s worth because deals on experience products are often promoted by new merchants (Wang, Zhao, and Li, 2013). Yet in the online platform, consumers can update their imperfect knowledge by observing others behavior, including the cumulative number of deals sold to preceding peers and the peer reviews as well as their ratings, which are often displayed prominently in real time. These observations may boost consumer arousal and confidence, both of which affect their purchase likelihood (Berger and Schwartz 2011; Luo 2009). Luo (2005) finds that social influence can significantly increase the urge to purchase. Since mobile devices are heavily used for online social interactions, m-WOM may further strengthen this impulsive urge to purchase. The consumer purchase process involves five stages: problem recognition, information search, evaluation of product options, purchase decision, and post-purchase support (Engel and Kollat 1978). WOM may have a significant effect on each of these stages. At the problem recognition stage, WOM can remind a consumer of the need for consumption and trigger the planned buying behavior process. In the information search stage, WOM allows promotion to be fully presented, which facilitates users’ access to and recall of promotion information. In the decision-making stage, WOM enables consumers to easily share information with others and solicit opinions from
friends and family members (Clemons, Gao, and Hitt 2010). It also allows scheduling and instant coordination with relevant others. In the purchase stage, mobile devices save users’ time and travel costs by providing instant online purchases with special discounts. It also provides a way to interact with other customers to help diminish cognitive dissonance.

3.3.3 Theoretical Background

In the third study, we draw from the theory of observational learning and social influence to examine the effect of real time reviews on deal purchase and redemption.

3.3.3.1 Observational Learning

Observational learning occurs through observing the behavior of others. It is a form of social learning which takes various forms, based on various processes. The theory of observational learning suggests that in making the participation decision, an individual infers the value of alternatives by observing the choices of her predecessors. A number of experimental studies provide empirical support that individuals tend to change their behavior based on the information about others’ behaviors. The concept of observational learning is also found in the consumer behavior literature. Researchers used reference group theories to explain why people tend to make purchase decisions based on the observation of others’ purchasing behaviors. (Zhang 2010; Zhang and Liu 2012). Prior studies also show that the action-based information provided in observational learning (e.g., realized sales volume and post consumption evaluation) is more credible and convincing than the attraction of deal discount. Thus,
observational learning should have a larger effect on sales, because “actions speak louder than words” (Liu 2006; Cheung et al. 2012).

3.3.3.2 Social Influence

Deutsch and Gerard (1955) were the first to distinguish two types of social influence, normative and informational influence. Normative influence occurs when a person conforms to expectations of another person or group, while informational influence is a learning process in which a person accepts information from others as evidence about reality. Park and Lessig (1977) further proposed the third type of influence by breaking the normative influence into two dimensions. The three types of social influence are (1) informational: observing others’ behaviors as a source of information so as to enhance their knowledge of a particular environment; (2) utilitarian: observations of others to ensure acceptance and avoid psychological or physical harm; and (3) value-expressiveness: observing others so as to match one’s self-image with the social world. With limited information available, when people observe the purchase actions of all previous consumers, this publicly observable information outweighs their own private information in shaping their beliefs. An information cascade can occur in that all subsequent observers will hold similar beliefs. As a result, people follow their predecessors’ actions and become engaged in a type of herd behavior (Banerjee 1992).

3.3.3.3 Construal level theory

Research on construal levels has been conducted in several other contexts to gain a deeper understanding on consumer judgment, decision making and consumption
related behavior. It demonstrates that buyers mainly consider the possibility of alternative set toward the event of near psychological distance (Malkoc et al. 2005; Leiser et al. 2008). Some examples include the effect on sensory effects of competing brands and brand extensions (Kardes, Cronley, and Kim 2006; Kim and John 2008), psychological distance and fluency of information (Alter and Oppenheimer 2008), and gambling and probability as a form of distance (Sagristano, Trope, and Liberman 2002; Wakslak, Trope, Liberman, and Alony 2006). When it is examined as an individual difference variable or personality characteristic, the research on construal levels show that consumers’ inherent construal level influence their decision making by “a preference for information, experiences, or events that match the individual’s abstract or concrete mindset” (Kim and John 2008). For instance, a person with an inherent concrete or low construal level tends to prefer information presented in more detailed, complex, incidental, and contextualized form. Therefore, consumers falling into this category tend to be influenced by detailed features of the information presented, as well as paying attention to the contextual details that are relevant at the moment. In contrast, consumers who use more abstract mental models construe stimuli with relatively simple, de-contextualized, and coherent representations that extract the general ideas from the available information (high-level construals). As a result, consumers with high levels of construal tend to be influenced by abstract and general features of information presented, such as clichéd characteristics that are the result of abstraction and generalization about the features of certain types of people, events, or
other information (Ashmore and Del Boca 1981; Hilton and von Hippel 1996). In this regard, understanding the effect of WOM on consumers’ evaluation of a deal and subsequent purchase behavior is critical in a fiercely competitive online marketplace.

3.3.3.4 In the Mobile Setting

With the rise of mobile technology and social media, the speed of information cascade formation and the time needed for herding is shortened by the instant feedback aggregation. In addition, m-WOM often represents a lower construal level since it is generated right after the experience on a device that is closer to the sender himself. For the receivers of WOM, they are also more interested in the information from closer social relations because they are more likely to have similar tastes (homophiles) or know about a person’s idiosyncratic tastes (tie strength). When the effect of tie strength interacts with the time and location proximity, they enable m-WOM to be more effective than traditional online WOM in influencing purchase decisions.

3.3.4 The Conceptual Framework

In the first two studies, we have examined the distinctive attributes of m-WOM and its key differences when compared with those from the desktop portal; we also discuss how these distinctions will the focal reader’s perception. Here the current framework focuses on 1) the influence of WOM on purchase of promotion deals adoption, 2) the effect of a deal’s discount rate; 3) the effect of device or platform, i.e., whether mobile WOM amplifies these effects.

We show that consumer construal level explains how consumers differentially evaluate
mobile content under varying contexts of social and temporal conditions, thereby leading to variance in the effect of WOM. Consumer purchase intentions are the highest when they are stimulated by social and temporal congruency information of the promotion. This occurs because shorter temporal and closer social relations induce consumers to mentally construe the promotional offer more concretely, trustworthy, which in turn increases their involvement and purchase intent.

**H12: m-WOM will have more influence on in-group consumers to adopt a promotion than d-WOM**

In addition, according to the recent research of contextual marketing, consumers often attach greater significance to events whose benefits are experienced immediately (Kenny and Marshall 2000; Prelec and Loewenstein 1991). In contrast, when events occur later in time, the contextual benefits are perceived as less valuable for immediate decision-making (Goodman and Malkoc 2013). Given the small screen sizes of mobile devices, consumers tend to use mobiles for immediate activities, so more-timely information would be perceived to be more effective to consumers (Molitor, Reichart, and Spann 2012). Thus, we hypothesize

**H13: m-WOM will also have greater influence on overall promotion adoption than d-WOM**

Past research has indicated that the uncertainty about deal quality is a key concern affecting consumer’s purchase behavior (Wang, Zhao, and Li 2013). The vivid display of promotion deal information boosts consumer arousal and increase consumer
attention to the deal (Bone 1995; Ye et al. 2013). According to the observation learning theory, enabling a focal consumer to observe the deal status and the reviews can create an information cascade with signals of promotion attractiveness and quality (Bandura 1977; Bikhchandani, Hirschleifer, and Welch 1998), which would reduce his or her uncertainty about a deal. As a result, popular deals can reduce consumers’ perceived risk of purchase. In addition, the social influence literature (Iyengar, Van den Bulte, and Valente 2011; McShane, Bradlow, and Berger 2012) suggests that observing the collective actions of prior buyers enable the focal customer to infer more accurate information about a promotion. If the worth of a deal is questionable, it will be less appealing to a potential buyer (Zhang and Liu 2012). The more popular a deal seems to be, the more likely a consumer may purchase it.

Since d-WOM tends to be longer, more descriptive, more cognitive, and normally distributed, consumers will find it more informative and diagnostic, thus helpful for minimizing the uncertainty associated with deals with deep discount. In contrast, when a deal offers a moderate discount, consumers will be less motivated to assess the deal worth via cognitive processing due to the lower level of perceived risk, which makes the m-WOM effective. Hence, we propose that deal discount rate will moderate the portal effect:

**H14a:** m-WOM will have more influence on promotions with lower discount than those with higher discount.

**H14b:** d-WOM will have more influence on promotions with higher discount and
those with lower discount.

3.3.5 Empirical Analysis

3.3.5.1 Data Description

Last year, Meituan and Dianping, China’s two largest group deals sites, confirmed that they were merged to create a dominant player in the nation’s booming market of O2O service and promotional deals. For our study, they provided a unique data set of promotions via different platforms. The value of these data is that they include the actual transaction records. The data they include public information of the deals (e.g., deal popularity, deal reviews, price, and savings), customer data (e.g., consumer purchase records, referral history, and social networks), and the consumption details (time of purchasing, purchase amount, time of posting WOM, and WOM detail at the user level)

The random sample of data encompasses the group buy records of 2014 and contains more than 20 businesses, 20 promotional deals and more than a hundred thousand transaction records. They come from two product categories, i.e., restaurant dining and car care services. Because consumer purchases and review intensity are time-varying by the day, the total number of observations in our database amounts to 113,795 at the customer-deal-month level. We also append the data of the customer reviews: review sentiments and other factors as control variables to enhance the model validity. Table 9 provides the collection detail
Table 9: Data Collection of Study Three

<table>
<thead>
<tr>
<th>Item</th>
<th>Amount</th>
<th>Note</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of deals</td>
<td>20</td>
<td>Promotional deal offered by businesses</td>
</tr>
<tr>
<td>No. of Business</td>
<td>20</td>
<td>Deal hosts</td>
</tr>
<tr>
<td>No. of Reviews</td>
<td>46,435</td>
<td>Reviews received for those 20 deals</td>
</tr>
<tr>
<td>No. of Adoption</td>
<td>113,796</td>
<td>Purchase rate of those 20 deals</td>
</tr>
<tr>
<td>Rank of Deal Duration</td>
<td>2-12</td>
<td>Validation Period (Month)</td>
</tr>
<tr>
<td>Rank of Discount</td>
<td>11%-90%</td>
<td>Discount rate of each deal</td>
</tr>
<tr>
<td>Rank of Price</td>
<td>20-1057</td>
<td>Retail Price</td>
</tr>
</tbody>
</table>

3.3.5.2 Methodology

To test our hypotheses, we employ Generalized Linear Mixed Model, also known as GLMM to estimate the effect of WOM on both friend’s adoption rate and deal’s overall sales performance. The generalized linear mixed model (GLMM) is a flexible generalization of ordinary linear regression that allows for response variables that have error distribution models other than a normal distribution. It is an extension of generalized linear models to include both fixed and random effects (hence mixed models). We model the actual amount of deal sold as the functions of WOM after controlling for consumer and deal specific variables.

We testing the influence of WOM by using time varying reviews’ attributes (number of WOM, WOM length, rating and sentiment) and deal popularity (number of deals sold). Although the data varies in terms on the validation period, we arrange the observation window at the monthly level. Hence, we test the WOM’s effect by using lagged time series to avoid the potential endogenous issue. We incorporate the temporal and social variables to further compare the effects of both portals. In the last,
we propose that discount rate and WOM portal will have an interactive in influencing the adoption of a deal. Thus, we add in the discount rate and the its interaction with the portal.

The dependent variable is number of deal sold at time T in a log form. We operationalized it as the log of "Purchase" received. Logarithmic transformations are a convenient means of transforming a highly skewed variable like ours into one that is more approximately normal.

The explanatory variables are WOM attributes including valence, length, emotional sentiment (density of affection and adverb), extremity, time span between the adoption and review posting; deal attributes including original price of that deal, amount of deal sold at previous time t-1, type of business; and the reviewer’s attributes, which most importantly is the number of reviewers’ friend who adopt the same promotion after seeing the deal reviews. Table 10 provides the detail elaboration of each variable.

<table>
<thead>
<tr>
<th>Table 10: Variable Definitions of Study Three</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable</td>
</tr>
<tr>
<td>Sales (log)</td>
</tr>
<tr>
<td>Fans Adoption</td>
</tr>
<tr>
<td>Temporal Distance</td>
</tr>
<tr>
<td>m-WOM</td>
</tr>
<tr>
<td>d-WOM</td>
</tr>
<tr>
<td>Type</td>
</tr>
<tr>
<td>Dependent</td>
</tr>
<tr>
<td>Dependent</td>
</tr>
<tr>
<td>Independent</td>
</tr>
<tr>
<td>Definition</td>
</tr>
<tr>
<td>A log form of positive integer value representing the number of deal sold in a certain month</td>
</tr>
<tr>
<td>A positive integer value representing the number of deal sold by reviewers friend in a certain month</td>
</tr>
<tr>
<td>A positive temporal integer represents the average time span between the adoption of deal and the review writing (days)</td>
</tr>
<tr>
<td>A positive integer value representing the number of m-WOM the deal received in a certain month</td>
</tr>
<tr>
<td>A positive integer value representing the number of d-WOM the deal received in a certain month</td>
</tr>
</tbody>
</table>
We then use the mean comparisons to compare the variables from both population and different portals on the promotion deals. The results below support and reconcile our previous finding that m-WOM also has its distinctive nature in the case of promotional deals when compared with the desktop ones, and in consequence, the friends’ adoption and overall sales performance of each deal also varies cross the different portals.

Table 11: Comparative Statistics of Study Three

<table>
<thead>
<tr>
<th>Variable</th>
<th>Population</th>
<th>Mobile</th>
<th>Desktop</th>
<th>Sig.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St.Dev.</td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>Sales (Log)</td>
<td>2.22</td>
<td>1.24</td>
<td>0.00</td>
<td>4.63</td>
</tr>
<tr>
<td>Fans Adoption</td>
<td>0.21</td>
<td>0.27</td>
<td>0.00</td>
<td>2.08</td>
</tr>
<tr>
<td>Temporal Distance</td>
<td>14.03</td>
<td>12.83</td>
<td>0.00</td>
<td>67.00</td>
</tr>
<tr>
<td>Number of WOM</td>
<td>170.59</td>
<td>297.29</td>
<td>0.00</td>
<td>1460</td>
</tr>
<tr>
<td>Length</td>
<td>21.42</td>
<td>18.77</td>
<td>0.00</td>
<td>103.00</td>
</tr>
<tr>
<td>Affection</td>
<td>1.00</td>
<td>2.83</td>
<td>0.00</td>
<td>29.17</td>
</tr>
<tr>
<td>Adverb</td>
<td>0.74</td>
<td>1.71</td>
<td>0.00</td>
<td>11.10</td>
</tr>
<tr>
<td>Valence</td>
<td>2.92</td>
<td>2.09</td>
<td>0.00</td>
<td>5.00</td>
</tr>
<tr>
<td>Deal Original Price</td>
<td>159.60</td>
<td>175.80</td>
<td>20.00</td>
<td>636.00</td>
</tr>
<tr>
<td>Deal Type</td>
<td>0.50</td>
<td>0.50</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Deal Sold (log)</td>
<td>3.00</td>
<td>1.17</td>
<td>0.85</td>
<td>5.49</td>
</tr>
<tr>
<td>Discount rate</td>
<td>0.58</td>
<td>0.26</td>
<td>0.10</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Notes: Population=425,418; Mobile=18,178; Desktop=7,240
Below equations specify our econometric models. Model 1 and 2 are the estimation of Hypothesis 12, we compare the different power of WOM from each portal to inspect whether m-WOM is more influential for the in-group friends’ adoption. Model 3 and 4 are the estimation of Hypothesis 13, which is the testimony of whether m-WOM is also more influential in the overall promotion deal sales. Lastly, Model 5 is the test on the interaction effect of deal discount and portal.

Log(Friends adoption) = \beta_0 \text{ (number of m-WOM)}_{t-1} + \beta_1 \text{ m-WOM attributes}_{t-1} + \beta_2 \text{Deal Popularity}_{t-1} + \beta_3 \text{ Deal attributes} + \epsilon \quad (1)

Log(Friends adoption) = \beta_0 \text{ (number of d-WOM)}_{t-1} + \beta_1 \text{ d-WOM attributes}_{t-1} + \beta_2 \text{Deal Popularity}_{t-1} + \beta_3 \text{ Deal attributes} + \epsilon \quad (2)

Log(Sales) = \beta_0 \text{ (number of m-WOM)}_{t-1} + \beta_1 \text{ m-WOM attributes}_{t-1} + \beta_2 \text{ Temporal Distance} + \beta_3 \text{ Deal attributes} + \beta_4 \text{ Deal Popularity}_{t-1} + \epsilon \quad (3)

Log(Sales) = \beta_0 \text{ (number of d-WOM)}_{t-1} + \beta_1 \text{ d-WOM attributes}_{t-1} + \beta_2 \text{ Temporal Distance} + \beta_3 \text{ Deal attributes} + \beta_4 \text{ Deal Popularity}_{t-1} + \epsilon \quad (4)

Log(Sales) = \beta_0 \text{ (number of m-WOM)}_{t-1} + \beta_1 \text{(number of d-WOM)}_{t-1} + \beta_2 \text{ m-WOM attributes}_{t-1} + \beta_3 \text{ d-WOM attributes}_{t-1} + \beta_4 \text{ Temporal Distance} + \beta_5 \text{ Deal attributes} + \beta_6 \text{ Deal sold}_{t-1} + \beta_7 \text{ Discount rate} + \beta_8 \text{ Discount rate x Portal} + \epsilon \quad (5)

3.3.5.3 Analytical Results

In our GLMM model, it shows that m-WOM will positively influence the friend’s adoption rate and m-WOM’s influence is stronger than d-WOM (\beta=0.054 vs 0.002). Secondly, m-WOM is also triumph the d-WOM in the effectiveness of overall sales of promotion deal (\beta=0.026 vs 0.011). Lastly, we hypothesize that the effect of reviews on promotion sales will vary depending on both the review portal and the deal discount.
We find that discount rate is positively correlated with deal sales, it can be explained that normally, consumer will find those moderate discount (i.e. 10% off discount rate 90%) is consider to be less suspicious and safe to adopt. We also include interaction terms between review portal and discount rate. The result supports our expectation that the relationship between promotion discount rate and purchase exhibits an interaction, for deals with moderate discount, m-WOM will be more influential while d-WOM will be more influential for deals with extreme discount rates.

Table 12: Estimation Result of Friend’s Adoption and Deal Sales Function (GLMM)

<table>
<thead>
<tr>
<th>DV: Friend's Adoption</th>
<th>DV: Sales(log)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
</tr>
<tr>
<td>Number of m-WOM</td>
<td>0.054**</td>
</tr>
<tr>
<td>Number of d-WOM</td>
<td>0.002*</td>
</tr>
<tr>
<td>Length</td>
<td>0.03*</td>
</tr>
<tr>
<td>Affection</td>
<td>-0.026</td>
</tr>
<tr>
<td>Adverb</td>
<td>-0.05</td>
</tr>
<tr>
<td>Valence</td>
<td>0.14</td>
</tr>
<tr>
<td>Deal Popularity(log)</td>
<td>0.35**</td>
</tr>
<tr>
<td>Deal Type</td>
<td>-0.21</td>
</tr>
<tr>
<td>Deal original Price</td>
<td>-0.002</td>
</tr>
<tr>
<td>Discount rate</td>
<td>2.11**</td>
</tr>
<tr>
<td>Temporal Distance</td>
<td>-0.005*</td>
</tr>
<tr>
<td>Discount rate x Portal</td>
<td></td>
</tr>
</tbody>
</table>

Note: Sample=240 (20deal *12month) **p<.01 *p<.05

3.3.6 Conclusions

Study three examines the effect of m-WOM at the final consumption stage. It highlights the importance of m-WOM in the product purchase and revenue generation and provides meaningful implications for mobile marketing. We draw on the construal level perspective to hypothesize how different attributes of WOM affect consumer
responses to promotions and why and when m-WOM is effective at this stage.

Because most promotion deals are offered by new merchants with varied discount rates, consumers may be uncertain about a deal’s worth. Yet consumers may infer the quality and desirability of a deal by observing how others perceive the deal. In this sense, the more discussions in the community, the more likely consumers will be to partake of it. Our analyses of a unique data set confirm that observational learning and social influence affect actual consumption and these effects are different depending on the portal of WOM and deal worth (discount rate).

Mobile is ostensibly a research area of growing interest, so is for the adoption of mobile communication technologies among consumers and businesses (Ghose and Han 2014). Despite the great interest in mobile commerce, there is a dearth of research on the effect of WOM on promotions in the mobile setting. Prior research (Kauffman and Wang 2001; Li and Wu 2013) investigated consumption activities without consumer level data. We extend our research to the mobile setting by using the aggregated consumer data and identify an asymmetric portal effect in terms of the different discount rate. We also advance the literature on behavioral attitudes and adoption of mobile promotions (Bruner and Kumar 2005; Provost 2011) by assessing the effect of WOM on the sales of promotion deals. We utilize the purchase records data from dianping.com to triangulate the empirical evidence. Our work finds that the effect of WOM can be amplified on mobile device and m-WOM is especially effective when a deal offers a moderate discount; long descriptive reviews from desktop, on the
other hand, are more convincing for deals with extreme higher discount rates. It provides valuable insight into mobile marketing. Given the tremendous impact of consumer reviews, a comprehensive understanding of the effect of their thoughts on purchase behaviors may appease the negative concerns (Edelman, Jaffe, and Kominers 2012).

From a tactical perspective, we provide additional suggestions beyond simply making deal information visible to consumers on a website. To merchants, to increase deal sales, they should not only display the amount of deals sold but also encourage more WOM upon the deal offer. For example, a well-established business may offer a moderate discount deal, may encourage more instant feedback right after the consumption. Those new businesses may want to boost the sales by offering big discount, invite for more detailed and descriptive reviews from consumers after their consumption.
Chapter 4

Research Findings and General Discussion

4.1. Summary of Findings

Constant access to mobile technology has become a norm for consumers. In addition to using mobile devices to gather product information, make purchases, watch video, and read news, consumers increasingly use mobile devices to share their product experiences with others. Mobile word-of-mouth marketing has already shown its emergence in terms of driving business growth and effectiveness. Although some are excited about these developments, others are concerned about the potential negative implications of real-time word of mouth. Empirical investigation of this subject is lacking in the literature. More generally, there is an interest in understanding how the growing use of mobile technology will change the content of consumer word of mouth and the consequential impact on the purchase-related decisions. This research thus represents an attempt to address these issues. In particular, we examine the distinctive characters of mobile word-of-mouth and its impact on consumption behaviors. In the following sections we will discuss the key findings, and then address the limitations of these studies, and conclude with the implications for both theory and practice.

In the first study, we propose that differences in the way in which mobile and desktop word of mouth are created will lead to variations in the content of mobile and desktop
word of mouth. Our conceptual model identifies those factors that lead to differences in content: time constrains, physical movement, attention span, device screen size and a lower construal level. A real-time creation process that affects the likelihood that consumers reflect on their experiences, the construal level at which word of mouth is written; a smaller device factor that makes it more difficult to create extensive word of mouth yet increases accessibility and therefore the likelihood of engaging in word of mouth; and a more personal relationship between the consumer and device that changes the type of language used in word of mouth. Based on these factors, we develop a set of hypotheses and test them on a unique set of data of reviews created on mobile and desktop platforms. Our results show a number of important differences in the characteristics of m-WOM. In support of the idea that the real-time creation process reduces reflection and small keyboards and screens make it more difficult to create content on mobile devices, we find that content created on mobile devices are by nature more abstract, shorter and more extreme. In support of the idea that mobile device is taken more as a self-extension and reflects more personal opinions rather than for social broadcasting, m-WOM is generated more by common consumers rather than experts for those inexpensive products.

Some of these content differences should increase the value of mobile word of mouth while others may decrease its perceived value. In our second study, our empirical results provide evidence for these mixed effects on helpfulness. WOM is generally perceived to be more helpful when they are temporally and socially closer to the
receiver. This effect is more amplified for mobile content; it is also valued more for hedonic consumption while its counterpart of desktop reviews is more helpful for utilitarian consumption.

In the third study, the finding demonstrated the m-WOM’s distinctive effect on sales of promotional deals. It is the same scenario that m-WOM is more effective for both friend’s adoption and deal sales. For discounts or price promotions, they have a greater influence on the adoption of moderate discount offers but desktop reviews are more effective in promoting deals of deeper discount.

The findings contribute to the growing literature on the role of m-WOM in affecting the perceptions and the consumption behaviors and help business owners to effectively improve performance by utilizing this seamless interaction.

4.2 Theoretical Implications

From a theoretical standpoint, the results contribute to the existing literature in a number of ways. First, the paper makes a contribution to mobile marketing literature by empirically investigating mobile word-of-mouth and providing insight into the drivers of mobile effects. The findings have shown the robustness of our model and the effectiveness of an integrated method in mobile research. Second, this research specifies an explicit structure for the influence of WOM on consumer behavior in the mobile context. It has demonstrated the validity of existing theories and extend them into the mobile setting.
4.2.1 Media Richness Theory and Compensatory Adaptation Theory

Media Richness Theory is a framework to describe a communications medium by its ability to reproduce the information sent over it. This theory highlights the extent to which a medium is capable of sending rich information as well as the proposition that media use is most adequate if the medium is matched with the complexity of the task at hand. The theory is mostly used in study how and why people choose a certain media to accommodate their communication needs. It is used to rank and evaluate the richness of certain communication media. According to the principle of compensatory adaptation, electronic communication media users can adapt their behavior in such a way as to overcome some of the limitations of those media. That is, individuals who choose to use electronic communication media to accomplish complex collaborative tasks may compensate for the cognitive obstacles associated with the lack of naturalness of the media.

Recent research on foraging in e-commerce (DiClemente and Hantula 2003; Hantula et al. 2008; Rajala and Hantula 2000; Smith and Hantula 2003) and Internet information search (Pirolli 2007; Pirolli and Card 1999) has bring innovative and valuable insights in understanding the interactions with new technologies. Our research further extends it to the mobile context and confirms that by using mobile device, our content generation and consumption behavior has further evolved, and the communication need is well compensated by some mobile functions such as real-time interactions.
4.2.2 Construal Level Theory

Construal level theory (Liberman and Trope 2008) has emerged as a “leading contemporary theory” in the fields of social psychology and consumer behavior. However, this theoretical perspective has not yet been widely applied to the study of media psychology and mobile marketing. Construal level theory refers to the degree of abstraction at which events, objects, or people are represented in the cognitive hierarchy. High-level construals are general, relatively abstract, and schematic, decontextualized, and superordinate mental representations, while low level construals are specific, detailed, concrete, unstructured, contextualized, subordinate mental representations (Trope and Liberman 2010). It holds that we tend to think about close items more concretely and far items more abstractly (Trope and Liberman 2010). Construal level theory informs how message creators can effectively construct and deliver persuasive messages and how receivers will successfully process messages.

We extend this leading theory to the mobile study and argue that the primary concepts associated with construal level theory are conceptually related to several features of m-WOM. Mobile phones and other portable devices are an extension of ourselves rather than a fixed device tied to a place. Therefore, the awareness of lower construal level will be amplified by using them to generate and consume content. When using mobile devices, consumers’ perception of construal level will be drawn even closer and they will be more likely to see m-WOM as socially and temporally closer than desktop ones.
4.2.3 Observational Learning and Social Influence

The theory of observational learning suggests that in making the participation decisions, an individual infers the value of alternatives by observing the choices of her predecessors. Observational learning occurs through observing the behavior of others. It is a form of social learning which takes various forms, based on various processes.

The concept of observation learning is also found in the consumer behavior literature. Researchers used reference group theories to explain why people tend to make purchase decisions based on the observation of others’ purchasing behaviors. (Zhang 2010; Zhang and Liu 2012).

With limited information available, people observe the purchase actions of all previous consumers. This publicly observed information outweighs their own private information in shaping their beliefs. An information cascade can occur, in that all subsequent observers will hold similar beliefs. As a result, people follow their predecessors’ actions and become engaged in a type of herd behavior (Banerjee 1992).

With the rise of mobile technology and social media, the speed of information cascade formation and the time needed for herding will be shortened. When the tie strength is multiplied with the time and location proximity, these enable m-WOM to be more effective than traditional online WOM in influencing purchase decisions. Our study integrates Observational Learning and Social Influence to examine the effect of WOM from mobile devices.
4.3 Managerial Implications

Although the findings of this study bring some useful implications for researchers, several practical implications can also be drawn for practitioners. The rapid proliferation of mobile phones and other mobile devices has created a new channel for marketing in the ubiquitous environment. For managers, this research provides important insights into how increased use of mobile platforms is likely to lead to differences in the characteristics and influence of consumer created content. Marketers who seek to understand and capitalize on this new content need to account for these differences.

Our findings suggest that it is important to understand how real-time effect, smaller size, and more personal user-device relations are likely to change the content and value of mobile word of mouth. Understanding these differences is important to marketers who seek insight and who wish to determine how to best respond to mobile consumers. Our results support the idea that mobile word of mouth is created in real-time using devices that are both harder to generate content than traditional desktop or laptop computers; yet they are more accessible and more personal. Real-time reactions may not persist for a long time. In this way, mobile word of mouth may provide fewer insights into consumer cognitions or have long-term impact on their attitudes. On the other hand, the mobile enhanced functions like easy way of emotional expression (emoji), locational check-in and easy photo-sharing compensate the insufficiency and offer customers a more vivid and reliable content for reading. Mining mobile word of
mouth and using mobile devices for market research may be better for products for which real-time responses are desired or for which consumers are unlikely to invest substantial cognitive resources. Furthermore, we found m-WOM is more generated by those common consumers rather than experts or foodies who are more cautious on their social image and express their opinion with meticulous wording-editing; and those shorter and narrative expressions concentrate on inexpensive consumption.

We further investigate the m-WOM’s perceived value. Our findings show that WOM is more helpful when it is socially and temporally closer and this effect is amplified by using the mobile device. Further, we show that consumers also perceive the helpfulness of WOM differently, depending on the type of product. In other words, product type can moderate the influence of review portal on perceived review helpfulness.

In the last study of consumption behavior, we focus on the friend’s adoption and deal sales. We find that m-WOM triumph the effectiveness in both influencing friends and overall sales performance. M-WOM is also more effective when a deal offers a moderate discount; and desktop reviews are more influential for deals with higher discount rate.

Although real-time consumer attitudes may not persist, their word of mouth will. Marketers need to face this trend and address these concerns by 1) encouraging reviews with more on-site photos and locational check-in information to compensate for the abstractness; 2) suggesting timely reviews depending on the price level and
product category; 3) inviting more in-group spreading by using mobile apps like WeChat or Line after m-WOM is generated; 4) focusing on deals with moderate (lower) discount for group-buying. When competing with the business who offers higher discount, managers can encourage more real-time m-WOM to arouse the emotion and enhance the deal attractiveness. Since deeper discount offers take more cognitive effort to reduce uncertainty descriptive WOM from desktop devices is more valuable.

4.4 Limitations and Future Research

Here, we highlight the limitations of this study that could be addressed in future research. This research is an initial attempt to conceptually identify and empirically test the differences in the content and value of mobile word of mouth. There are a number of opportunities to expand this work empirically and conceptually. First of all, this study was conducted using data from mainland China. Thus, the generalization of our findings to other economic contexts should be made with caution. Second, to test our hypotheses, we take advantage of a unique dataset that includes consumers who use both mobile and non-mobile platforms to create content. Our dataset uses word of mouth from one platform for restaurants and car caring, product categories that involve both hedonic and utilitarian consumption. We have chosen a single mobile application for investigation, which help to minimize the variation due to different mobile reviews platforms. However, we suggest future research re-examines the model in other mobile contexts to determine whether it can be modified or improved. Future research could test these ideas on more platforms and in the laboratory or field experiments. Thirdly,
in our conceptual model, we focus on the use of mobile platforms to generate word of mouth. Future research could expand these ideas to examine which products are most likely to be evaluated and purchased on mobile devices, how individual and contextual factors—including demographic and location—are likely to moderate these effects; and what is the most effective way for business owners to respond to these m-WOM (the time, the manner, the frequency). Other researchers could examine how the use of mobile platforms for information creation and consumption can be integrated with other platforms and how other factors such as product lifecycle and location affect consumer behavior.

Continuous changes in consumer technologies may provide other research opportunities. For example, Google Glass and Apple Pay offers opportunities to examine how augmented reality affects consumer decision making. Future wearable devices should provide consumers with additional information that will be combined with information from the physical environment. VR technology may also allow consumers to share the entirety of their product experiences with others. Future research could examine how such immersive content has different effects on the receivers than the text-based and reflective word of mouth.

4.5 Conclusions

The starting point for our consideration was the fact that understanding the attributes, the value and the effectiveness of m-WOM. In this paper we explored the phenomenon by using media psychology and behavioral economics to better understand the
strengths, limitations and the effect of m-WOM. We derived a number of determinants that influence behavior in the mobile setting and presented three studies to investigate these effects.

The major impact of the framework is threefold. First, it investigates a rare explored area in mobile research. Second, it helps marketers to better understand the critical value, both pros and cons of m-WOM and allows predicting how to realize their full potential. Third, the proposed theories provide researchers a useful first step to better understand the users’ behavior in mobile setting.

In summary, this study provides several valuable insights in understanding the effects of m-WOM characteristics in ubiquitous decision making. With the proliferation of mobile devices such as the iPhone and iPad and other wearable gears, mobile word-of-mouth has shown its value for business growth. In this regard a deeper understanding behind their decisions to engage in mobile word-of-mouth communication is useful, and even necessary.

As new technologies continue to change the consumer experience, and the ways in which consumers communicate these experiences to others, marketers will face new opportunities to gain insight as well as challenges to meet consumer needs. Future research could continue to enrich this line of research by considering the impact of technological development on the effect of mobile word-of-mouth effectiveness from both the recipient and sender perspectives.
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