2015

Social Media Networks: The Social Influence of Sentiment Content in Online Conversations on Dynamic Patterns of Adoption and Diffusion

Tung Cu
Louisiana State University and Agricultural and Mechanical College

SOCIAL MEDIA NETWORKS:
THE SOCIAL INFLUENCE OF SENTIMENT CONTENT IN ONLINE CONVERSATIONS ON DYNAMIC PATTERNS OF ADOPTION AND DIFFUSION

A Dissertation

Submitted to the Graduate Faculty of the
Louisiana State University and
Agricultural and Mechanical College
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

in

The Department of Information Systems and Decision Sciences

by
Tung Cu
M.B.A., Asian Institute of Technology, 1999
Ph.D., Old Dominion University, 2008
August 2015

ACKNOWLEDGEMENTS

The author extends his gratitude to all involved, some way or the other whose contribution brought the dissertation to this stage. Specially, the dissertation chairman, Professor Helmut Schneider, whose inspiration, guidance, suggestions, constant encouragement and care not only as the dissertation committee chairperson but also as a supporter, deserves the author's gratefulness. The author extends his esteem and appreciation to the dissertation committee member, Professor James Van Scotter, whose creative ideas, valuable suggestions and helpful comments enhanced the value of this work. Sincere thanks also go to the dissertation committee member, Professor William Black for his invaluable advice and effort guiding the author to develop an innovative research method of the dissertation.

All the respondents and contributors for the work in data collection period in the social networking site used in the study are acknowledged for their valuable help, prompt responses and interest. Many thanks give to the friends at LSU Ourso College of Business and in the author's home country for their help. All the friends here at LSU deserve thanks for their love and supports during the research project. The fellow Ph.D. students are never to be forgotten. The author expresses his love to all of them.

The author is grateful and extends his thanks to the LSU Graduate School for its one-year financial support and to the LSU Department of Information Systems and Decision Sciences for its continuous supports during the entire study at Louisiana State University.

Encouragement and support from parents and relatives are keys to the success of this work. Last but not the least, support, patience and dedication from my beautiful wife and my lovely son are the secret of the whole success.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The current study is focusing on diffusion and adoption of new digital artifacts. The goal is to explore the social role of user-generated content (UGC) during the diffusion process of digital artifacts in the context of online social networks. The study spans a wide range of analytics methods and tools such as predictive modeling, latent sentiment analysis, data retrieval, and other tools of time-series analysis & visualization. Data collection is conducted on 260 new digital products and more than 105 thousand social network nodes. Results of the study provide a deeper insight into the influence of textual UGC sentiment on new product diffusion and how such a web system (i.e.: online social networks) can help to enable a process of value co-creation. The overall finding shows that Volume of Post and UGC Sentiment have a dynamic impact on Diffusion (Adoption Rate) of digital products. But, the relationships among them depend on certain situations.

Specifically, UGC Sentiment has a dynamic impact on Adoption Rate in the early stage of the diffusion process. That is UGC Sentiment and Adoption Rate have a reciprocal relationship during the early stage. However, this relationship was faded out in the later stage. Volume of Post has a positive impact on Adoption Rate throughout the process. Both UGC Sentiment and Volume of Post are also more likely to influence on a single-generation and successful product than a multiple-generation product. Surprisingly, Depth of Post and Ratings did not play a significant role in the diffusion process.

The study sheds light on the crowding power and the long-tail effect in online social networks. Findings also offer valuable implications for organizations to set up their strategic vision in terms of targeted marketing, customer relationship management, and information dissemination.

INTRODUCTION

It has become clear that Online Social Networks (OSNs) have grown to be one of the most prominent forms of communication of our time. In September 2012, Facebook reached a milestone of one billion active users (The Wall Street Journal, Oct. 2012) – a number only slightly less than the population of India (1.2 billion) and more than triple the population of the United States (315 million). At the same time, 10 hours of content was uploaded to YouTube every minute and, in the last year, people sent an average of 140 million Tweets each day. OSNs are a collective power that will "change the way the world changes". John Rendon, the president of Rendon Group, a global strategic communications consultancy, says "the game changer" is "user-created content."[1]

OSNs are notable in that they allow the creation and exchange of User Generated Content or UGC (Kaplan & Haenlein, 2010), and as such have become a tool for bringing together small contributions from millions of people, making their contributions matter (Time Magazine, 25 December, 2006). According to Forrester Research, 75% of Internet users join social networks to generate and/or consume content such as reading blogs, sharing news, or contributing to product reviews. This trend is no longer limited to teenagers, but now also includes older generations. It is therefore reasonable to say that User Generated Content (UGC) is an important subject for many individuals and organizations who want to make profitable use of OSNs.

Generally, the IS literature related to UGC in OSNs has focused on the following two streams:

[1] User-generated content has the same meaning

The first stream of research has primarily focused on content management, including the amount of content and how to encourage participation in content generation. For example, some researchers have argued that Internet users are more likely to respond to simpler messages and to generate simpler responses as the overloading of mass interaction grows (Jones, Ravid, & Rafaeli, 2004). Others have found a difference between OSNs with structural designs that favor identity-based versus bond-based attachments on content generation. One example being that community participants in the identity condition contributed more content and visited their community twice as frequently as participants in the bond condition (Yuqing Ren, Kraut, & Kiesler, 2007). Recently, scholars have paid more attention to the content itself and have started to appreciate its influence on users' online behavior. Abbasi and Chen suggested that research on content influence should consider four different types of textual content including topical, event, sentiment, and affect (Abbasi & Chen, 2008). Cao and his colleagues found that more extreme product reviews can receive more votes of helpfulness (Cao, Duan, & Gan, 2011. Luwig et al. (2013) and Sridhar et al. (2012) further investigated the relationship between textual content & writing styles on product reviews and online purchasing. However, their findings showed major conflicts regarding the role of textual content in shaping purchase intention (Ludwig et al., 2013; Sridhar & Srinivasan, 2012).

The second stream of research focuses on the adoption of new products and diffusion in OSNs and covers topics such as social opinion leaders, the influence of social ties, the impact of OSN structure, and the measurement of diffusion. Goldenberg and his colleagues showed that while it is widely thought that experts lead the adoption of radical innovations, social opinion leaders

may actually be more effective. Likewise, Nair et al. documented that physician prescription behavior was significantly influenced by the behavior of research-active specialists, or "opinion leaders," in the physician's reference group. A recent study found that social ties influence OSN users' uploading behavior. It showed that when social ties are being formed, members of dyads begin to upload more similar photos than they did before, and after a social tie is formed, this similarity evolved in different ways in different subgroups of dyads (Zeng & Wei, 2012). Similarly, other studies investigated the role of a dual-network structure in facilitating content exploration. These studies showed that exposure to YouTube's dual network results in a more effective exploration process (average product rating, overall satisfaction) and thus increases the rate of new product (videos) adoption (Goldenberg, Oestreicher-Singer, & Reichman, 2012; Susarla, Oh, & Tan, 2012).

Although scholars from IS and other disciplines have started to become aware of a big gap between these two streams, previous studies have been limited on the relationship between product reviews and purchase intention (Ludwig et al., 2013). No prior research has truly filled the gap between the two research streams. To fill this gap, we conduct a study focusing on the social role of UGC in the process of digital product diffusion.

We organize the remainder of this study as follows: we begin by introducing the current status of diffusion research and what makes our study different from previous research. Next, dynamic relationships between UGC metrics and diffusion are hypothesized. We then describe our modeling approach and the methodology to conduct the study. We present out empirical analysis of data. Finally, we offer implications for theory and mangers before suggesting future research.

RESEARCH QUESTION

By nature, communications and interactions between OSN users are not direct, but are mediated via online textual posts and comments. This results in electronic Word-of-Mouth (eWOM), transmitted exclusively through user-generated content (UGC). As shown above, the literature confirms that this UGC has contributed to different aspects of business performance. Examples of relevant UGC include reviews and movie revenue, mood and public vote, chatting and stock performance, and affective content and purchase conversion.

Previous studies have found that the volume of such posts is the strongest predictor of user behavior, while traditional WOM theories posit that sentiment within conversations is the primary factor influencing individual behavior (Kozinets, de Valck, Wojnicki, & Wilner, 2010). Interestingly, the relationship between sentiment and diffusion in OSNs has been ignored by previous studies. Until now, it has not been understood how UGC sentiment influences product adoption and diffusion in OSNs.

In the current study, we aim to *empirically document the role of user-generated content (UGC) in shaping dynamic patterns of digital product diffusion in online social networks (OSN)*. This study is concerned with the following research questions:

- How does UGC sentiment shape dynamic patterns of digital product diffusion in OSN?
- To what extent does user-generated content explain digital product diffusion in the early stage and in the later stage?
- How does a characteristic such as single versus multiple generation affect digital product diffusion?

Scope of the Study

The current study seeks to explore the social role of UGC in the diffusion process of a digital product in the context of online social networks. Since the domain of this research concerns diffusion, it is advantageous to limit the scope of the study to new products rather than innovations. Although there is a distinction between a new product and an innovation, this study argues that most of the key structural and conceptual assumptions of models related to the diffusion of innovations can be well applied towards new product diffusion (Mahajan & Wind, 1986). The scope of the study is also limited by the communication channel of the diffusion phenomena. Unlike previous research, the current study observes new product diffusion in a virtual world. It is assumed that the adoption behavior of online users is mostly influenced and driven by online forces, but not offline factors. This is especially true when we limit the scope further into a specific OSN – a video game social network where users have to register for a membership to consume and exchange UGC. Such an OSN helps to set up a field study characterized by a close setting consisting of only like-minded people.

LITERATURE REVIEW

DIFFUSION CONCEPT

Diffusion of a new product is a phenomenon that occurs in many social networking systems. It can be considered as the process in which a non-adopter is transformed into an adopter of a new product over time. By definition, *diffusion is the process in which an innovation (a new product in this study) is communicated through certain channels over time among the members of a social system* (Rogers, 1983).

A common agreement within the diffusion literature is that in order for diffusion of a new product to occur, it requires the presence of four main elements which are the *new product* (or service) itself, *communication channels*, *time*, and a *social system*. These elements are identifiable in all diffusion research and in every diffusion campaign or program.

A *new product* or service in the context of innovation is an idea, practice, or object that is perceived as new by an individual or other unit of adoption. The new product differs significantly in terms of features or intended uses from any previous product existing in the market. The degree of its newness is “objectively” measured by the lapse of time since its first use or discovery. A new digital product can be in the form of hardware, software, or both. Examples of hardware are DVDs, personal computers, and mobile phones, while video games, operating systems, and utility programs are examples of software.

A *communication channel* is the medium by which information is conveyed from one individual to another. Usually, online communication tends to share some common features with offline communication such as generating and sharing messages with one another in order to reach a mutual understanding. The literature considers diffusion as a special form of communication in which a new idea, practice, or object is shared. The essence of the diffusion process is that information about a new idea is disseminated from one person to another person or several others. The primary party is an individual or a subject of adoption who has knowledge of or an experience with using the new product. The secondary parties are those who do not yet have knowledge of or experience with the new product. A communication channel is what connects the primary and secondary parties. While mass media channels usually play a quicker and more efficient role in creating product knowledge and awareness to a group of potential adopters, interpersonal channels usually do better in terms of persuading an individual to accept the new product. This is especially true if the interpersonal channel links two or more like-minded individuals who have similar socioeconomic status, education, or share common interests in product categories or other important personality traits. Online social networks can retain features from both mass media and interpersonal communication channels. Thus, the diffusion process in OSNs continuously proliferates thank to mass communication as well as persuasion.

Time is the third and an important element in the diffusion process. By nature, diffusion reflects a series of users' behavioral adoption across different moments in time. The time dimension simply matters and should be taken into account as a strength in diffusion research. In the past, however, much of diffusion research lacks a time element or the measurement of the time dimension was distorted because researchers often relied on the respondents' recall when they

adopted the new product. The time dimension is involved in diffusion in two ways. First, a potential adopter passes from their first awareness of the new product to complexity expectation, then to newness evaluation, and finally to adoption or rejection (Wood & Moreau, 2006). Second, each member within a certain system has their own relative earliness/lateness of adoption when compared with other members of the system. This difference in time reveals the rate of adoption within the system, and can be measured as the number of members who adopt the new product in a given time period.

A *social system* is defined as a set of interrelated units that are engaged in joint problem solving to accomplish a common goal. By definition, members or units of a system may be individuals, informal groups, organizations, and/or subsystems. The OSN system analyzed in the current study consists the registered members, forum moderators, journal editors, game producers, advertisers and game suppliers. Each OSN user is assumed to be distinguished from other users. Acting as like-minded people, they cooperate at least to the extent of seeking to build a virtual world of all common interests for every member. This mutual goal connects participants together and keeps the system afloat. Social system characteristics such as structure and norms affect the new product diffusion in several ways. Social structure – the patterned arrangements of strong and weak links among members – gives regularity and stability to diffusion patterns throughout the system. It can decrease the uncertainty of information flow and make adopting behavior predictable to some degree. Past research has investigates how system norms affect the rate of new product adoption. While structure reflects link patterns, norms illustrate the established behavior patterns among members. Norms serve as a guide or standard for members' behavior and thus may become a barrier to change which, in turn, can hinder adoption rate.

DIFFUSION MODELS

Single vs. Multiple Generation

The Bass diffusion model is one of the most recognized models for explaining product diffusion patterns and predicting market demands. However, the model only considers a monopoly case or the industry as a whole where no competition affects the diffusion process of the product. The idea of multi-generation diffusion was introduced in the first time by Norton and Bass in 1987. Their model deals with the dynamic sales behavior of successive generations on high-technology products (Norton & Bass, 1987). Kim, Chang, and Shocker (2000) further extend this model by defining the market potential as a function of sales revenue from other categories. Other studies start to explore the multi-generation characteristic of diffusion (Altinkemer & Wenqi, 2008; Danaher, Hardie, & Putsis Jr, 2001).

One vs Two-step Model

The original theory of communication adopts the one-step model or "hypodermic" that treated individuals as atomized objects of media influence. The theory assumes that media influence directly flows to individuals. In contrast, the two-step model assumes that individuals may be influenced more by exposure to each other than to the media. By the late 1970s, the two-step flow had become the "dominant paradigm" of media communication.

In the two-step diffusion, Watts and Dodds (2007) found that prestige users in social networks play an important role in the first stage of diffusion. Watts and Dodds (2007) also found that large cascades of influence are driven not by influencers but by a critical mass of easily influenced individuals. The modified theory of UGC network coproduction (Kozinets et al., 2010; Watts & Dodds, 2007) also posits that there is cross-communication among members of a social network to co-produce value and meaning and thus create multiple micro steps of diffusion within the social network.

Dimensions of Diffusion

There are three metrics of diffusion: *adoption rate*, *diffusion depth*, and *diffusion breadth*. The main measure of diffusion in the current study is *adoption rate* which is the number of adoptions per period (Rogers, 2003). It is generally measured as the number of individuals who adopt a new product in a specified period, such as weekly in the current study.

The phenomena of diffusion can also be reflected via diffusion breadth and diffusion depth. *Diffusion breadth* reflects how quickly a new idea disseminates inside a social network. In other words, the metric measures the size of the adopter's network. *Diffusion depth* reflects the average usage intensity of the adopter base (Mahajan, Muller, & Wind, 2000).

USER-GENERATED CONTENT REVIEW

Current Trends in UGC Research

Current trends in UGC research primarily pay attention to three main streams. The first focuses on the economic value of UGC. Studies in this stream explore the impact of UGC on business benefits such as stock returns, sales conversion, box office revenues, price premium, usage behavior, and so on (Dellarocas, Zhang, & Awad, 2007; Forman, Ghose, & Wiesenfeld, 2008; Ludwig et al., 2013; Pavlou & Dimoka, 2006; Rishika, Kumar, Janakiraman, & Bezawada, 2012; Tirunillai & Tellis, 2012).

The second trend consists of studies focusing on quantitative UGC and/or qualitative UGC. Early research in this stream mainly investigates the role of numerical evaluations and ratings about a new product (Moe & Trusov, 2011; Sridhar & Srinivasan, 2012; Wood & Moreau, 2006). Gradually, UGC studies are increasingly giving attention to qualitative assessments and the relationships among different UGC forms (Cao et al., 2011; Korfiatis, García-Bariocanal, & Sánchez-Alonso, 2012; Mudambi & Schuff, 2010).

The third trend discusses UGC dissemination among Internet users. Some studies explore online users' propensity and/or motivation to contribute their UGC under the influences of previous posted UGC and product characteristics (Dellarocas, Gao, & Narayan, 2010; Zhu & Zhang, 2010). Other studies have started to develop a theory of UGC diffusion inside social networks (Kozinets et al., 2010; Watts & Dodds, 2007). Still, other recent studies look for ways to explain

how UGC diffuses among Internet users (Susarla et al., 2012) and how to measure information diffusion (Garg, Smith, & Telang, 2011; Godes & Mayzlin, 2004).

While taking the ideas of the second and third trends into account, the current study extends the first trend by undertaking a large scale sentiment analysis of more than 93K UGC reviews and discussions in order to hypothesize and empirically assess the role of UGC sentiment on diffusion of a new digital product.

UGC and Business Performance

The relationship between UGC and business performance has long received wide attention across disciplines ranging from politics, economics, marketing, management and information systems. A number of scholars have investigated various aspects of business performance such as reviews and movie revenue (Dellarocas et al., 2007; Liu, 2006); review and sales or sale ranking (Chevalier & Mayzlin, 2006; Gu, Park, & Konana, 2012; Zhu & Zhang, 2010); affective content and sales conversion (Ludwig et al., 2013); user rating and software market share (Duan, Gu, & Whinston, 2009); Twitter sentiment, public mood, and voting behavior (Bollen, Mao, & Pepe, 2011); and chatting and stock performance (Tirunillai & Tellis, 2012).

For example, Tirunillai and Tellis (2012) examines whether UGC is related to stock market performance. They claim that volume of post has the strongest positive effect on abnormal returns and trading volume. More importantly, there is an asymmetric effect between negative and positive metrics of UGC on abnormal returns. Whereas negative UGC has a significant

negative effect on abnormal returns with a short “wear-in” and long “wear-out,” positive UGC has no significant effect on these metrics.

Bollen et al. (2011) conducts a sentiment analysis on all half-year tweets published on Twitter in order to extract six mood states of the public. Their results indicate that events in the social, political, cultural and economic sphere do have a significant and immediate effect on various dimensions of public mood.

Dellarocas et al. (2010) found that consumers prefer to post reviews for products that are less available and less successful in the market. At the same time, however, they are also more likely to post reviews for products that many other people have already commented on online. The presence of these two opposite forces leads to a U-shaped relationship between a population’s average propensity to review a movie post-consumption and that movie’s box office revenues: moviegoers appear to be more likely to contribute reviews for very obscure movies but also for very high-grossing movies. Sharing similar results, Moe and Trusov (2011) found that consumer online product ratings reflect both the customers’ experience with the product and the influence of others’ ratings. Past research shows that although rating behavior is significantly influenced by previously posted ratings and can directly improve sales, the effects are relatively short lived once indirect effects are considered.

Ludwig et al. (2013) studied the semantic content and linguistic style properties of verbatim customer reviews on conversion rate. Their research reveals that the influence of positive affective content on conversion rates is asymmetrical, such that greater increases in positive

affective content in customer reviews have a smaller effect on subsequent increases in conversion rate.

Table 23 in the appendix briefly reviews previous empirical research in terms of research subject, research site, method or model, independent variable, dependent variable, and general findings. The earliest study on the effect of UGC on business performance is related to box office revenue (Liu, 2006) and then was followed by some other studies concerning the same movie product category (Dellarocas et al., 2010; Dellarocas et al., 2007). Researchers have examined the conditions under which people are more likely to rely on others' opinions to watch a movie, the motivations for different viewers to contribute post-consumption online reviews, and the main predictors to forecast goo entertainment sales. Data were mostly collected from Yahoo! Movies, an open discussion forum where everyone can post movie-related reviews or comments. Although, by nature, data sets for these studies are time series, multiple regression or least square models were used for analysis instead of a time-series model.

Other studies use logit demand and time-series models as an alternative perspective, typically taking into account network effects on UGC from adopting behavior over time (Moe & Trusov, 2011). Research subjects are not limited to one product line such as movies, but extend to multiple product categories ranging across books, personal care, and digital products. Although researchers have recognized the explanatory power of textual UGC (Zhu & Zhang, 2010), most of previous studies in this group paid more attention to numerical UGC rather than textual UGC due to the imperfections of text analysis programs (Chevalier & Mayzlin, 2006).

Thanks to a dramatic advance in the algorithm of sentiment analysis, recent studies have included textual UGC to explain the variance of business performance (Tirunillai & Tellis, 2012). Time-series models are the most popular and the vector auto-regression (VAR) procedure is the main technique to specify parameters of time-series variables. However, readers seldom see social contagion or diffusion models in these studies (Bass, 1969; Coleman, Katz, & Menzel, 1966). Although the effects of UGC on business performance has received wide attention from the academic community, it is a surprise that little, if any, research has been done to explore the dynamic relationship between textual UGC and diffusion. Therefore, the purpose of the current study is to fill this gap by integrating UGC variables into the original diffusion model to explain the dynamic patterns of the relationship between UGC sentiment and new product diffusion.

CURRENT VS. PREVIOUS RESEARCH

So, what really makes the current study different from previous research? Past research has found some connections between UGC and business performance. However, previous studies have not yet looked deeply inside the relationship between UGC sentiment and diffusion. Table 1 shows gaps from previous studies and how the current study differs from past research.

The current study is different from previous research in several ways. It is the first to empirically demonstrate the dynamic impact of UGC sentiment on diffusion across different new digital products. The results imply that firms' targeted online UGC may not be effective throughout the entirety of the new product's life cycle, regardless of if the product has an older version or not. This implication contrasts with the extant view that firms should constantly manipulate online

UGC sentiment to boost its business performance such as sales and revenues, given the great efficiency of social media networks in disseminating information. However, the influence of UGC sentiment becomes greater immediately after the new product is introduced and becomes less important in the later stage of the product's life cycle (PLC). This implies that while the relationship between UGC sentiment and diffusion in the early stage is a reciprocal causality, their relationship in the later stage is more correlational than causal. In addition to time-dependent tactics to managing UGC, firms should also strategically respond to UGC across product features differently between multiple-generation products (i.e.: incremental innovation) and single-generation products (radical innovation). This result suggests that first-product and/or single-product category producers should be more concerned about UGC sentiment and UGC manipulations because UGC could significantly impact their business performance.

Unlike previous studies, which focus on the aggregative response of business indicators such as sales, revenues, or stock performance, the current research investigates specific responses of adoption rate (diffusion) under each change of UGC sentiment. To this end, the current study proposes a diffusion model and, for the first time ever, states a hypothesized relationship between UGC sentiment and diffusion. It also illustrates how a product's features and its life cycle status moderate potential adopters' reliance on UGC and thus they play an important role in governing the efficacy of UGC. While past research applies sales forecasting models and thus assumes a long lasting PLC curve, the current study takes into account the influence of the first and second orders of previous adoption rates. This approach not only helps researchers determine the PLC start and end stages, but can also integrate the multiple-generation feature of the new product into an extension.

Table 1: Gaps from previous studies and differences b/w current and previous studies

	Previous studies	**Current study**
Proposed Model	Assume a long lasting curve of product sales or stock returns	Consider product life cycle as start and end via a diffusion model
	Assume only one version products	Consider multiple version products
Dependent Variable	Use sales or ranking aggregation as dependent variable → not a true diffusion unless we assume a single purchase for each user. Ranking may reflect a marketing purpose of the website owner	Use number of adopters over time as dependent variable → reflect a true adoption rate considering all social/environmental impact.
UGC Variable	Most studies just look at the rating metrics rather than textual comments.	Users give helpful rating → that means they read online reviews.
	Only few look at textual opinions of users	Use latent sentiment analysis
Sampling Site	Use data sources from Amazon, Cnet, or Epinion → one-way interaction b/w reviewers and readers → different from common social networks with multiple-way interaction (Schweidel, Moe, & Boudreaux, 2011)	Use data source from a video game social network where people can exchange ideas via multiple-way communication.
	Most adopters are lurker → the causality b/w UGC collected and adopting behavior is weak	Adopters are the member of the online social network
	Ignore relationship b/w reviewers and readers/adopters	Social users may have different relationships with others
Sampling Method	Use snowball approach to collect data	Use systematic sampling to collect data

Most of previous studies use sales or sale ranking aggregation as a dependent variable. However, sale ranking may reflect a marketing tactic of the website owner to purposefully polish a product or a group of products. Sales and revenue are not a true proxy of new product diffusion unless we assume that it is enough for a consumer to purchase the product only one time (Mahajan & Peterson, 1985). This sounds right in some circumstances, but it is problematic if we extend the construct to include diffusion depth and diffusion breadth. To fix the problem, this study uses adopter-based differences over time as the dependent variable. The proxy does not overlap the breadth and depth dimensions and truly reflects diffusion as it measures adoption rate, considering all social and environmental impacts. Regarding independent variables, such a quantitative UGC metric as product rating is one of the key independent variables in early UGC-business performance studies. However, recent research found that consumers' ratings in product reviews depends on how helpful it is to support their adopting decision. This indicates that consumers carefully read online reviews before making their decision because the richness of content in the review can provide consumers with more information about the new product. Thus, the current study emphasizes the qualitative aspect of UGC and uses latent sentiment analysis to quantify UGC sentiment.

Previous studies often use data sources from Amazon, Cnet, or Epinion, Most readers of these websites are lurkers and only have a one-way interaction with product reviewers. Such an approach ignores the social relationship between reviewers and potential adopters. The lack of interaction among these Internet users may weaken the causality between UGC and business performance (Schweidel et al., 2011). Also different from past research, this study collects data

from a social network dedicated to online video games where users have to register before they can tap into community benefits and exchange ideas about new products. Potential adopters are members of this online social network and can interact with existing adopters via multiple-way communications. By that way, causality between UGC and diffusion is observed and controlled, correctly reflecting the influence of UGC sentiment on consumers' adopting behavior.

Collecting diffusion data is highly time-consuming and one of the most difficult phases in this kind of research. Normal solutions of past studies are either purchasing data from commercial data providers or using a snowball method to gather data needed. Although purchasing data is acceptable for a study to be published, there is little or no control on how accurate the data is to serve the research purpose. The snowball sampling is not a random approach and thus, it can cause bias toward the first respondent or group of respondents from which the data is drawn. To solve these problems, our empirical strategy explicitly controls for sampling bias by applying a systematic method of data collection inside a pre-determined social network. The method is conducted via several steps. First, after treating the list of all members of the website as the sampling frame, the sampling starts by randomly selecting a respondent from the list. Then, eliminating the same number of the next members in the ordered sampling frame, a new respondent is selected to be included in the sample. The process is repeated till the list ends. This method ensures that every member of the population has a known and equal probability of selection. Thus, the sampling bias is avoided.

HYPOTHESIS DEVELOPMENT

This section focuses on the detailed relationship between UGC sentiment and diffusion.

UGC SENTIMENT AND ADOPTION BEHAVIOR

When it comes to deciding whether or not to adopt a new product, people may rely on their own knowledge when comparing benefits against costs and risks. But when facing some level of uncertainty, they can also look to external sources to help make their decision. The literature on social media networks suggests that peer-to-peer influence is one of the strongest influences on users' behavior (Bickart & Schindler, 2001). This form of social influence can occur when User-Generated Content, usually in a textual form, is used as a medium to transfer ideas from one individual to another. In such cases, users' emotional states can be evoked when they are reading product feedback or comments containing sentiment content (Lau-Gesk & Meyers-Levy, 2009). This is congruent with psychological research that shows that people rely on feelings when making judgments (Greifeneder, Bless, & Pham, 2011). In addition, affective content can influence their thoughts and behaviors which lead to changes in their judgment of products (Andrade, 2005; Lench, Flores, & Bench, 2011; Wood & Moreau, 2006). Thus, UGC with sentiment on a new product can effect an online users' decision to use that product.

As pointed out in previous studies, users often look for product ratings as one of the quantitative indicators about a product's value. But, they are also interested in some qualitative comments, especially in the case where the product has many features or functions that they want to learn

about (Korfiatis et al., 2012). Users are usually attracted to informative reviews or reviews with congruent tone. This also applies in the case of affective tone when there is a mood-congruent direction (Gorn, Tuan Pham, & Yatming Sin, 2001). The number of reviews a product receives also influences users' judgment and their final decision to adopt the new product (Mudambi & Schuff, 2010).

When reading reviews, users are interested in those that clearly express positive (pros) or negative (cons) aspects about the product (Cao et al., 2011). Such content sentiment may influence their attitude towards the new product, but the intensity of their attitude can be dependent on their motivation to search for available information. When there is a lack of external sources, the motivation is high. And when there are multiple information sources, the motivation is low. When the diffusion process moves from the initial stage to a declined stage, the amount of available information can vastly change. Thus, this affects the motivation of searching for product usage and may make the role of UGC sentiment more or less important in the decision to adopt the new product.

UGC Sentiment as an Indicator of Diffusion

UGC Sentiment could predict the diffusion of a new product for several reasons:

First, past research on UGC has shown that the intensity of textual sentiment (valence) can have a significant impact on review helpfulness and eventually on the sales of physical goods (Ludwig et al., 2013; Pan & Zhang, 2011). The sales of physical goods can be considered diffusion when

we assume that consumers only bought the new product one time. Diffusion can be considered a measure of business performance and it strongly correlates with sales and market share (Garber, Goldenberg, Libai, & Muller, 2004).

Second, if the firm had a transparent process of new product development, all information about the new product would be available immediately and completely for all potential adopters. However, information on the new product is usually only available periodically (e.g. monthly or quarterly) via the company's or third party's sources which is not prompt. Users can also rely on product information from mass media or consumer reports from industry analysts, which are also only available at a slow pace. Unlike these sources, UGC can be collected at a relatively fast pace and even up-to-the-minute, as shown in the data collection section of the current study. Thus, UGC sentiment could represent hot news and rich information about the product performance and it could make the digitalized product more viral (Berger & Milkman, 2012).

Third, in the information age, potential adopters are increasingly overwhelmed with the amount of information they receive every day. A number of them do not have the time or effort to filter the product of interest from all the noise. They usually look for helpful summaries or evaluations on the pros and cons of the product (Cao et al., 2011; Mudambi & Schuff, 2010). Moreover, a previous study regarding review-length data suggests that online users read comment text rather than relying only on summary statistics (Chevalier & Mayzlin, 2006). Written UGC provides relevant information for potential adopters because it is a direct expression of current users' personal experience and uncovers feedback on products that may not be evident in third party reports or experts' reviews in the media.

Fourth, past research has shown that users rely more on information from other users' rather than from the company's official channel. Consumers have developed a general tendency to disbelieve or be skeptical toward marketing messages. The reason is that UGC is more up-to-date and more objective because it is provided by non-employees (Goh, Heng, & Lin, 2013). Information generated by the firm typically describes product information based on technical specifications and is thus product-oriented, whereas UGC tends to describe a product based on usage conditions from a real user's perspective and is, in contrast, more likely to be consumer-oriented (Bickart & Schindler, 2001). Although many new product providers have developed communication channels and have offered various forms of product trials, these usage demonstrations can only reflect a small fraction of real conditions.

The above reasons clearly indicate that UGC sentiment is a good candidate for predicting the diffusion of a new product. However, the impact may not be instant, but delayed and can have feedback from the diffusion process. Unlike traditional word of mouth that is faded out in voicing communication, online UGC in social networks are recorded and presented for anyone who is interested in the new product. Thus, the UGC posted after the product's introduction can stay for a long time and could have an impact on a potential adopter weeks after the posted date (Chevalier & Mayzlin, 2006).

Moreover, existing adopters who have bought the product might chat about it on the social network they are a member of. Other potential adopters who are uninformed or who are undecided about which brand to buy may consult UGC sentiment before finalizing their decision.

The online reviews and discussion could subsequently affect their decision. At the aggregate level, these decisions would translate into adoption rate. However, it might take anywhere from a few days to a few weeks for UGC sentiment to reflect in the adoption rate because of several reasons. First, online users have to develop trust towards online reviews from strangers whom they have never met before. They need time to extract and digest the information they can count on. Second, usage complexity, especially in the case of high involvement products, might cause uncertainty, risk, and unforeseen costs for adopters. UGC sentiment itself has to take time to diffuse among social network users, and thus slow down the diffusion process.

Reverse impact of new product diffusion on UGC sentiment may also happen. This process begins with the first group of adopters when available information does not yet exist. Usually, the majority of early adopters are active members of the social network. They are motivated to post their reviews and discussions about the new product. Depending on how viral these reviews are, UGC sentiment can evolve strongly or weakly. Some potential adopters might be impressed by the overwhelming sentiment and quickly adopt the new product. Other potential adopters might take time to search for more product reviews from different sources enabling them to compare their anticipation of new product perception with the external sentiment before making their decision. Other factors such as product price and availability also contribute to the delay of adopting the new product.

Therefore, we believe that *UGC Sentiment has a dynamic relationship with Diffusion (Adoption Rate) and that it might take time for UGC Sentiment to truly effect Diffusion and vice versa*.

Early vs. Late Adoption Stage

Previous studies have treated the role of UGC sentiment equally throughout the diffusion process as they assumed a one-stage diffusion process. However, as shown above, when the diffusion process moves from the initial stage to a declined stage, the amount of available information can vastly change. This affects the motivation of searching for product comments and may make the role of UGC sentiment more or less important in the decision to adopt the new product (Ludwig et al., 2013).

For example, during the early stage, users might rely more on UGC comments and reviews due to lack of other available information. Then, over time, more and more informational sources become available. Social network users can then consult these other sources to make their decision. At this point, UGC Sentiment might still impact potential adopters, but it might not be as significant as it was in the early stage.

Additionally, UGC sentiment embedded in later reviews might not reflect adoption rate, but rather they only duplicate the opinion of reviews from the early stage. In a two-stage diffusion process, prestige users in social networks play important role in the early stage of the diffusion process and the large cascades of adoption in the second stage are driven not by influencers but by a critical mass of easily influenced individuals (Susarla et al., 2012; Watts & Dodds, 2007). Moreover, online product reviews reflect the influence of others' reviews. Past research shows that reviewing behavior is significantly influenced by previously posted reviews and can directly improve business performance (Dellarocas et al., 2010; Moe & Trusov, 2011). Previous UGC studies also found that frequent social network users give comments in first few weeks rather

than in later weeks in an attempt to gain prestige and credibility (Dellarocas et al., 2007; Liu, 2006). Thus, in the first stage, UGC reviews that reflect the true tastes of the population are more likely to go viral and reflect the adopters' decision (Ludwig et al., 2013). Then, in the second stage, the number of reviews and discussion reduces dramatically. Thus, the impact of UGC sentiment on diffusion may disappear or not be as strong as before.

Therefore, we believe that *UGC Sentiment could cause stronger responses of diffusion in the early stage, rather than the later stage of the diffusion process*. Note that the analysis drawn from this statement will apply to the first half (50%) of adoption and then second half (50%) of adoption.

SINGLE VS. MULTIPLE-GENERATION PRODUCTS

A multi-generation product is usually more popular than other totally new products because it has a larger base of adopters from the previous generation. Since potential adopters receive early notice about the launch of a new generation, some portion of adopters of current generation may prefer to wait for the new generation. They might know much about the new product and rely on their experience with the previous generation to make their decision.

Previous studies have shown that online users prefer to post reviews for products that are less available and less successful in the market. At the same time, however, they are also more likely to contribute reviews for products that many other people have already commented on online.

Online users appear to be more likely to contribute reviews for very vague products but also for very high-grossing products (Dellarocas et al., 2010; Zhu & Zhang, 2010).

New and single-generation products usually share very few features with existing products. This stimulates more curiosity and emotion among potential users. First-time product users found it is difficult to use these products effectively due to several factors. Users' learning curve is stiff for such kind of products because users are not educated in advance, or guidelines and supporting services are imperfect, or the new product itself is not user friendly. This might cause emotional discrepancy for early adopters and they are more likely to post extreme semantic reviews about the product to get more credits (Korfiatis et al., 2012). Moreover, extreme UGC sentiment about a product may go viral because people have high expectations, but a lack of real information about the product (Berger & Milkman, 2012) and thus it has a stronger effect on adopting behavior. In contrast, multiple-generation products create a portfolio of product performance which produces a more stable response from the user base. Although UGC virality may also occur in the case of multiple-generation products, it is less likely to stimulate users' adoption.

Since the impact of UGC Sentiment on Diffusion varies depending on whether the product is completely new or if it is the next generation of an established product, we believes that *a response of Diffusion to a shock of UGC Sentiment can last longer for a single-generation product than for a multiple-generation product*.

MODEL DEVELOPMENT

We will explain the development of our model in several steps. First, we describe a general model showing the relationship between user-generated content and business performance. Next, the Bass model is used as a starting point and then decomposed into different components to explain how it can be extended. Third, the addition terms of sentiment are introduced and integrated into the model. Finally, grouping and control variables are added.

GENERAL MODEL

The main objective of this study is to investigate the relationship between the Diffusion of a digital product at time t and user-generated content including Sentiment, Volume of Post, Depth of Post, and Rating at time t-i. Therefore, the general model reflecting this statement is as below:

$$\text{Diffusion (Adoption Rate)} = \text{f(Past Adoption \& User-Generated Content)} \qquad (1)$$

$$\begin{aligned} \text{Diffusion}_{t} = \alpha_0 &+ \alpha_1 \text{ (Adoption)}_{t-1} \\ &+ \beta_1 \text{ (UGC Sentiment)}_{t-i} \\ &+ \beta_2 \text{ (Volume of Post)}_{t-i} \\ &+ \beta_3 \text{ (Depth of Post)}_{t-i} \\ &+ \beta_4 \text{ (Rating)}_{t-i} \\ &+ \xi \text{ (Unobserved Variables)}_{t} \end{aligned}$$

Where:

Diffusion (Adoption Rate): new adopters in a period of time

Past Adoption: accumulative number of adopters in the previous time

UGC Sentiment: total valence of reviews, messages, or comments

Volume of Post: total amount of reviews, messages, or comments

Depth of Post: average content richness of reviews, messages, or comments

Rating (of Community): average rating score of the new product

By nature, diffusion or adoption rate is a phenomenon that evolves over time. Thus, it is expected that diffusion at time t significantly depends on diffusion at t-1. It is also believed that the variance of diffusion at a certain time is largely explained by the diffusion from a previous time. Note that we use the index t-i to indicate the delayed (lag) effect of UGC on Diffusion as discussed in the previous section.

BASS (1969)MODEL

In 1969, Bass proposed the first model of new product diffusion

$$dY/dt = Y_t - Y_{t-1} = [p + (q/m)Y_{t-1}](m - Y_{t-1}) = p(m - Y_{t-1}) + (q/m)Y_{t-1}(m - Y_{t-1}) \qquad (2)$$

Where:

dY/dt: adoption rate (diffusion)

m: total market potential

Yt: accumulative number of adopters at t

p,q: adoption parameters

The first part of the model captures adoptions due to users who are not influenced by the number of people who already have adopted the product, while the second part is adoptions due to users who are influenced by existing adopters via internal influence (Bass, 1969; Mahajan, Muller, & Bass, 1990). The second term shows the interaction of potential adopters ($m – Y_{t-1}$) and existing adopters Y_{t-1}. There is another way to interpret the Bass model. The diffusion rate is in general a function of all potential adopters taken into account of all factors that can theoretically transform a non-adopter into an adopter.

$$
\begin{aligned}
dY/dt = f(m - Y_{t-1}) &= \text{influence of existing adopters } (Y_{t-1}) + \text{influence of all other factors } (p) \\
&= (q/m)Y_{t-1}(m - Y_{t-1}) + p(m - Y_{t-1})
\end{aligned}
$$

EFFECTS OF UGC SENTIMENT TERM

According to Mahajan and Wind (1986), the word of mouth effect is captured by the interaction of those potential adopters ($m – Y_{t-1}$) who have not yet made an adoption and the power of persuasion. The theories of media richness and media promotion/advertisement also support this notion.

Since textual UGC is basically a form of communication somewhat similar to word of mouth, the internal influence consists of two different parts: UGC created by social network members including existing adopters via their sentiment reviews and UGC created elsewhere. In this study, we assume that external UGC will contribute to the model (1) via the unobserved variables term.

When fit into the Bass model, the effect of UGC sentiment on potential adopters ($m – Y_{t-1}$) can be considered as a sentiment influence (p') among other factors (p) and will contribute to the adoption rate. Therefore, to include the sentiment term, the extension of the Bass model is as below:

$$Y_t - Y_{t-1} = (q/m)Y_{t-1}(m - Y_{t-1}) + p(m - Y_{t-1}) + p'(\text{UGC Sentiment})_{t-i} \tag{3}$$

In addition, potential adopters might be also be attracted by the number of reviews and discussion of the new product, which indicates its viral power. Thus, there is a good reason to argue that Volume of Post might also contribute to the diffusion model and create an effect on adoption rate.

$$Y_t - Y_{t-1} = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-1}^2 + \beta_{11}(\text{UGC Sentiment})_{t-i} + \beta_{12}(\text{Volume of Post})_{t-i} + \xi_{,t} \tag{4}$$

Past research shows that there is relationships between content richness, changes in rating and changes in revenue. Therefore, we add the terms (Depth of Post) and (Rating) into the equation.

$$Y_t - Y_{t-1} = \alpha_0 + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-1}^2 + \beta_{11}(\text{UGC Sentiment})_{t-i} + \beta_{12}(\text{Volume of Post})_{t-i} \tag{5}$$
$$+ \beta_{13}(\text{Depth of Post})_{t-i} + \beta_{14}(\text{Rating})_{t-i} + \xi_{,t}$$

GROUPING TERMS

Dummy variables with values of 0 and 1 will be used to express the generation characteristic of video games, in which the value of 1 reflects a multiple-generation game, while the value of 0 indicates a completely new game.

OTHER CONTROLS AND EXTENSION

In the industry of video games, the market potential *m* of a game is determined by the market share of the platform the game is running on. Thus, to control this problem, we divide both sides of the equation (2) by m_j, the market size of a specific platform j at time t.

METHODOLOGY

This section describes the research design, variable measures, data collection, and data processing serving for the section of data analysis.

RESEARCH DESIGN

The following subsections explain the selection of the study site, the sampling of time, subjects, and sources of media content.

Selecting the Study Site

We selected the study site on several criteria to ensure the feasibility, validity, and reliability of the study. That being said, the video game industry was selected for several reasons. First, video games are one of the most popular digitalized products. The video game industry is currently growing much faster than any other entertainment industry such as game apps, music, and movies. Academic communities also pay a large attention to video game-related topics. Second, a video game can be classified as high-involvement product. Thus, the role of reviews is potentially greater for video games than for other types of digitalized products such as game apps, movies and music. A video game typically costs around $38.36 according to NPD Fun Group (2007). Given most gamers are young and have limited incomes, a game purchase is an important decision for a gamer. There are a high number of game titles released every week and they can belong to many different genres. Although most video game websites provide a search engine and a game library, game players still need to invest substantial time and energy to

identify good games among so many similar choices. Moreover, video games generally contain rich content because it usually takes up to the whole week for a player to conquer one. Therefore, reading game reviews is quite important for gamers to avoid bad purchases and wasted time from playing a boring game (Zhu & Zhang, 2010).

The current study follow the Chau and Xu (2012)'s framework to identify the explicit social network site of video games. Specific steps are as below:

- Step 1: Identify communities of the topic of interest
- Step 2: Collect information about users
- Step 3: Analyze content
- Step 4: Analyze interaction

To select the study site, we use the following criteria. First, the website must have rich data on textual UGC across the time period of investigation. Second, users' adoptions over time should be countable. Third, players' reviews and discussion which signal the product's diffusion, have to be retrievable. Using these criteria leads us to select the gaming website IGN.com.

IGN formerly known as Imagine Games Network is the flagship entertainment website of IGN Entertainment which positions its services on premium gaming & entertainment content. The website first aims to attract a male segment of 18-34 years old. Then, it extends to anyone who is 18+ years old. IGN's main website comprises several specialty sites or "channels". Each of them manages a subdomain and covers a specific area of entertainment; including major video game platforms, and other forms of entertainment such as films, television and other media. It is one of

the largest video game and entertainment social networks with a very high internet traffic, which means that 1 in 4 US men online visit IGN each month. The network attracts over 40 million unique visitors worldwide, including in US, U.K, Australia, Germany, and Japan.

Time Sampling

To extract the list of targeted video games, we first determined a time frame and then collected all game titles released within that time. We chose a one year round, from March 2012 to October 2012, for our analysis[2]. The reason being that the website went through a significant re-design during 2010-2011 and the accumulated adoption level of all video games is peak in 2012 compared with that of 2013 and 2014. The average life cycle of all games is approximately 33 months, but on average, more than 50% of game sales occur within the first four months and more than 90% within twelve months after a game's release (Zhu & Zhang, 2010). Moreover, textual UGC on the selected website is available before and after the time frame.

Because new video games are introduced in a weekly period, we choose a weekly analysis. Although both UGC and diffusion (adoption rate) become available at a very high frequency (up-to-the-minute), lower levels of aggregation (daily, hourly) do not provide more values for the study. Also, higher levels of aggregation (monthly or yearly) may lead to biased estimates due to a shortage of data series.

[2] The actual time for data collection extended to two years to cover one-year span for games released at the end of the year 2012.

UGC Sampling

The current study focuses on textual UGC[3] as the main source for sentiment. Although the website allows its members to post various content such as text, pictures, and videos, the proportion of video and picture to voice gamer opinions on products is small during the period under consideration. Since the website does not provide its members with a separate service for product reviews, gamers usually write their reviews and discussions along with the editorial reviews extensively for this purpose.

Table 2: Summary of Video Game Genre

Genre	No. Games	Reviews
Action	83	38348
Adventure	31	5910
Fighting	12	3885
Platformer	20	4819
Racing	11	1843
Role Play (RPG)	30	9894
Shooter	30	14699
Simulation	8	991
Sport	17	4267
Strategy	24	3105
Grand Total	266	87761

Moreover, unlike blogs and message boards, these reviews and discussions focus on video game evaluations, whereas blogs and message boards of the website usually discuss technical issues

[3] To simplify, UGC will be used for "textual" UGC for the remainder of the study.

and/or off topics about video games. Note that reviews and discussions are only available after the website opens an introduction page for the video game. These reviews and comments are accessible by all gamers and Internet readers. Table 2 displays a summary of video game genre and corresponding reviews.

Subject Sampling

We used a systematic sampling method to extract the list of gamers. IGN.com provides a specific search engine for its members to search for people (i.e.: gamer, editor, superstar etc.). The symbol “*” can be used to replace unknown letters. If we want to search for all usernames starting with “a”, we can type in the search engine “a*”. Each result page includes 10 usernames. To estimate the approximate total number of all IGN users, we search for all usernames starting with all numeric and alphabet letters. For example, the total number of “a*” usernames is 431756 listed in 43176 result pages, the total of “b*” usernames is 424342 listed in 42435 result pages, and so on.

The study use a step of 10 and randomly select the first page as a starting point. For example, when search for all usernames starting with “0”, the total number of result pages is 849. With a step of 10 and a randomized starting number of 9, the first result page to be collected is 9, the next page is 19 and so on. Table 21 in the appendix shows detailed summary of systematic sampling for subjects. Based on the above procedure, the social game network have 5,731,063 registered members. The initial sample extracted has a size of 676,491 members and the final sample consists of 105,463 members who has adopted at least one game.

MEASURES

This section describes the measures of independent variables (UGC), dependent variable (Diffusion), and control variables.

Measures of UGC

UGC can be characterized by several metrics (e.g., Liu (2006)). The current study restricts the analysis to four important metrics: UGC Sentiment, Volume of Post, Depth of Post and Community Rating. Each of these metrics is explained below.

Table 3: Examples of Term & Word Categories Used to Define Sentiment (Rule-Based)

Category	Examples
Affective Content	
Positive	Love, wow, <3, bitter sweet, pretty slick
Negative	Dumb, suck, pissed off, </3, hate
Entities	
Competitor	Microsoft, Sony, EA, Ubisoft
Platform	360, PS3, PC, Wii
Subject	Gamer, Review, Comment, Player
Products	
Graphic	Super HD (+), low quality (-), old (-)
Music	Fun (+), boring (-)
Story	Attractive (+), crappy (-)
Score	High (+), low (-)
Price	Cheap (+), over price (-)

UGC Sentiment

Sentiment of UGC refers to whether the overall comment is positive or negative towards a video game. Our measurement of UGC Sentiment combines all of the positive valence and negative valence of a product in a week's time. The procedure of a textual analysis to determine valence is explained in the Appendix section. The statistical algorithms used for the text classification are proven to be robust with SAS Sentiment Studio (Feldman, 2013). The sentiment analysis is presented in detail in the analysis section. Table 3 displays examples of term and word categories used to define sentiment (Rule-Based).

Volume of Post

Volume of Post refers to the total number of comments posted by gamers about a video game in a week. This measure reflects the magnitude of coverage received by the video game.

Community Rating

Ratings are the numerical assessment of the video game by gamers based on a numeric scale designed by the IGN website (on a scale of 1 (unbearable) to 10 (masterpiece). The study collects the aggregate rating of a game by taking the arithmetic mean of all the individual ratings each week.

Depth of Post

Average depth of post counts the average number of words in each review

Measures of Diffusion

Adoption Rate

The main measure of diffusion in the current study is adoption rate which count the number of new adopters in a period of time (week). The “weekly” unit is chosen because new video games are introduced weekly.

Past Adoption

The Bass diffusion model shows that adoption rate depends on both the first order and second order of its past adoption which is measured as the accumulative number of adopters in the previous time (t-1).

Note that as mentioned in the literature review, the phenomena of diffusion can also reflect via diffusion breadth and diffusion depth. However, due to the constraints of available data, we only focus on diffusion reflecting adoption rate. Future research may bring these measures into account and make this diffusion construct more complete.

Control Variables

Control variables consist of Volume of Post, average Rating and average Depth of Post. In addition, the Bass model suggests that the first order and the second order of diffusion in the previous period (t-1) should be included in the equation. See the model (2).

DATA COLLECTION

The current study uses a panel data over time with two dimensions: video games and gamers.

VIDEO GAME PROFILE

Since one of the units of analysis is a video game itself, this section describes the procedure used to collect the list of video games used in the study. The IGN website provides a search engine for Internet users to search for video game titles from A to Z. It also provides two types of filters: search by genre and search by platform. Search results can be sorted by title, publisher, IGN rating, and released date. We collected all video games released during the years of 2011-2014. The initial list included 7442 online video games for different consoles from IGN during 2011-2014 across the ten most popular genres which contain more than 98% of all video games IGN has introduced. Among these games, 6785 games have a valid date of release. The next step is to collect video game profiles since only a proportion of games received editorial introduction and corresponding gamer reviews and discussion. A Java script and a macro running on Internet browsers were used to fetch the home page of these games and then collected the information needed. From this list, video games that meet all of the criteria outlined in the methodology section were selected. This narrowed the sample to 282 games. However, to avoid result bias, some game titles released on multiple consoles were dropped, narrowing the sample further to 260 games. Since at least 6 data points are required to apply a time-series analysis, some games were dropped. The final sample consists of 154 game titles for time-series analysis. Table 22

shows the profile of video games in terms of genre and platform. See the Appendix for more details.

UGC SENTIMENT

Because it is not efficient to process UGC data manually, we used automated techniques for data collection and analysis. Here, we briefly outline the procedure adopted for data collection and preprocessing.

Because IGN does not provide an application programming interface (API) for data collection, we developed scripts to collect data from the website periodically. Based on the list of video games collected from the previous step, our scripts fetched the review page of each game. The textual content of each page was then stored in a folder at an individual level so that each review and discussion can be parsed and aggregated for sentiment analysis. In total, the UGC database sample contains 93,879 posts between March 2012 and October 2012.

GAMER PROFILE

Each member (gamer) in IGNs social network has their own homepage. Besides information about the number of followers the gamer has and who the gamer is following, the page also provides important information about the list of games the gamer has collected or wishes to collect. Whenever a game is collected, its title is added to the list. Thus, in order to count the adoption behavior of the gamer, the study used a small software or “crawler” to visit each

homepage weekly[4]. If the game title has appeared in the list, the crawler would mark this as an adoption and record the date and time of the adoption into a data file (excel tab comma format) containing one or more records. Figure 1 gives an example of gamer homepage.

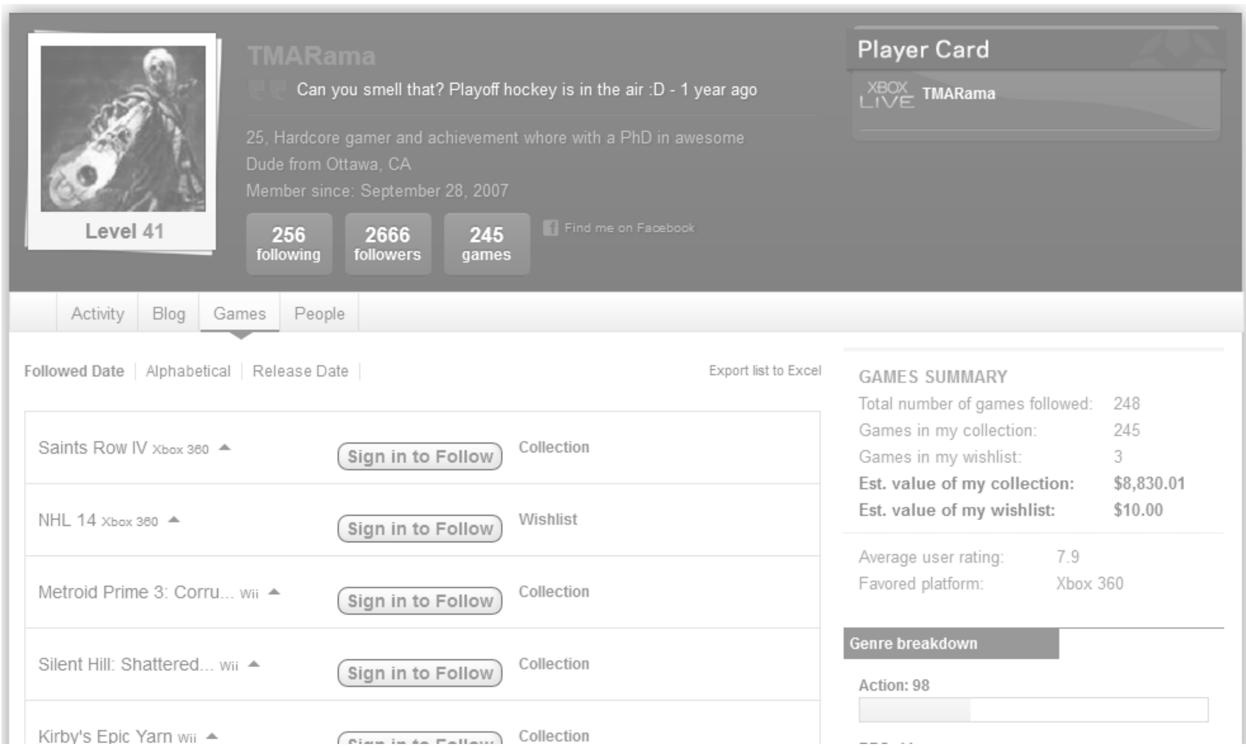

Figure 1: An example of Gamer homepage

[4] Actually, the crawler is able to collect data in real time. However, due to IT ethical rule, the crawler is deigned to visit only one page each minute.

DATA PROCESSING

We used SAS Enterprise software for a major part of the data process and analysis. The below figure shows how data were processed in SAS Enterprise.

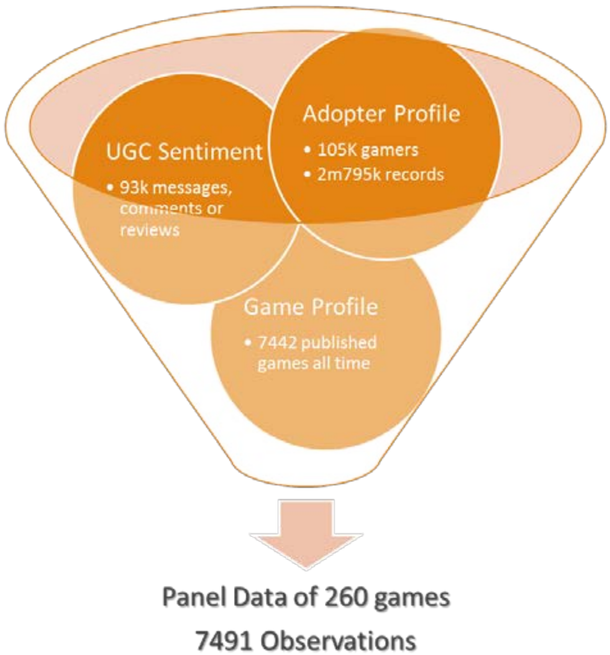

Figure 2: Data processing in SAS Enterprise

Diffusion Database

Since the crawler stores adoption information into 105K single-data files and the file name is the username of network members, it is necessary to combine these data files into one single database. To do this task, we wrote a small SAS program that is able to import and then append the 105K excel files into a large and single database in SAS. This amounted to 2 million and 809 thousand records. After all duplicate records were deleted, the total number was narrowed to 2

million and 795 thousand. The procedure also imported data files of Games Profile, Games Review, and Games Title into SAS Enterprise.

Sentiment Analysis

We used SAS Sentiment Studio software to quantify the sentiment of reviews and followed the procedure of UGC analysis proposed by Abbasi and Chen (2008).

To determine the degree of sentiment, we used two algorithms proven to be reliable for text classification in specific domains such as social networks: the naïve Bayesian classifier and the support vector machine classifier. More than 80% of review classifications are in agreement between the two algorithms. The details can be found in the Appendix.

We then had a group of raters[5] manually rate the UGC sentiment of 500 posts randomly selected from the 93,879 posts from the collected UGC database. Next, we conducted three different steps to arrive at the final model of sentiment. First, a statistical model on gamer reviews is applied. The statistical model determines if a review has positive or negative sentiment based on different algorithms. Then, a rule-based model is used on these reviews. The machine is fed with various words or phrases that signal positive or negative meanings. Finally, a hybrid model is applied to combine both statistical and rule-based models to arrive the final executive model for sentiment analysis. This model is then used to quantify the UGC sentiment of 93,879 posts in the database. See Table 3 in the previous section for more details.

[5] Students who attended one of the authors' classes.

Description of Data

As described above, raw data sets comes from IGN.com which is a subsidiary of Ziff Davis, Inc. Unlike previous studies, this work does not purchase data from commercial data providers. Instead, primary data were originally collected to avoid the many issues intrinsic to secondary data[6] provided by a third party. Since the study uses panel data for the model, the database includes three different data sets. The first data set provides individual information of gamers' adoption behavior including adopted game titles, platforms, publishers, ratings, adoption time, types of adoption, and user names. The data set contains 2,795,774 records of 105,454 members. The second data set gives detailed information on all past and current games offered by the site. The data includes game titles, publishers, publisher's ratings, release dates, genres, platforms, generation, average user scores, and previous scores (if any). The data set contains 7442 published and unpublished games from 2011 to 2014. The third data set consists of information from all reviews by gamers posted regarding the collected games. The data includes the poster's user name, date and time of the review, and review content. The data set contains 93,879 records posted by 24,108 online users. The combination yields a complete data set of 7,491 records for the time range between March 2012 and March 2014. While the first data set yields data for diffusion variables, the second data set yields data for control and grouping variables; and the third data set yields data for UGC sentiment variables. Table 4 displays summary statistics for the variables included in the model.

[6] A number of previous studies reported very correlations among variables (> 0.8)

Table 4: Descriptive statistics of variables in the time-series models.

Variable	Unit	N	Mean	Std Dev	Sum	Min	Max
Adoption Rate	Adoptions per week	7832	19.71	83.98	154395	0	3223
Past Adoption	Total previous adoptions	7832	644.66	1427	5049002	2.33	12310
Existing Adoption	Total current adoptions	7832	664.38	1453	5203397	2.33	12586
UGC Sentiment	Total valence per week	7832	5.31	60.71	41654	0	3259
Volume of Post	Total messages posted	7832	461.39	677.45	3613606	1.0	5796
Depth of Post	Avg. Words per message	7832	12.95	33.94	101457	0	1143
Rating	Avg. rating per week	7832	6.33	3.69	49537	0	10.0

The table shows substantial variation overtime in all variables of interest, which is a good sign to estimate the effects of independent variables on dependent variables. The number of data points counted is 7832. Unit of measure is weekly. Specifically, Adoption Rate counts the number of gamers adopting a video game per week. Past Adoption and Current Adoption illustrate the accumulative number of adopters in the previous and current weeks, respectively. UGC Sentiment is measured by a sum of valence per week, while Volume of Post is measured by a sum of all messages posted till the current week. Depth of Post counts the average number of words in messages posted per week. Rating is the average of scores gamers gave on a video game per week. Besides the descriptive statistics of variables, the study also performed Pearson correlations among them. Table 5 display correlations among variable in the model.

Table 5: Correlation among variables in the model

	Adoption Rate	**Past Adoption**	**Existing Adoption**	**UGC Sentiment**	**Volume of Post**	**Rating**	**Depth of Post**
Adoption Rate	1.00	0.28	0.33	0.13	0.09	0.08	0.05
Past Adoption	0.28	1.00	0.99	-0.03	0.20	0.17	-0.02*
Existing Adoption	0.33	0.99	1.00	-0.02	0.20	0.17	-0.01*
UGC Sentiment	0.13	-0.03	-0.02	1.00	0.11	0.04	0.06
Volume of Post	0.09	0.20	0.20	0.11	1.00	0.25	0.19
Rating	0.08	0.17	0.17	0.04	0.25	1.00	0.08
Depth of Post	0.05	-0.02*	-0.01*	0.06	0.19	0.08	1.00

* Not significant

From the results, most of correlations are significant. The sentiment rate positively correlates with adoption rate, while it negatively correlates with existing and previous adoption volume. This shows an agreement with the developed model in which past adoption has a negative coefficient.

EMPIRICAL RESULTS

The theory of diffusion of innovation implies that diffusion of a new digital product can be modeled as a time-series in which the current adoption rate is a function of the level and square of its past adoption. However, as shown in the section of *Model Development*, the diffusion phenomenon is not an independent stochastic process. It not only depends on internal forces of existing adopters, but also might be impacted by such external factors as comments and feedbacks. Therefore, the next task that arises is about testing hypothesized relationships between diffusion and its exogenous factors.

The empirical approach consists of six analysis steps. First, individual variables are tested for stationarity to see if the variables have a unit root and satisfy the assumption of ergodicity which means that the sample moments which are calculated on the basis of a time series with a finite number of observations converge in some ways for $T \rightarrow \infty$ against the corresponding moments of the population. In the second step, tests for endogeneity and the possibility for long-term (persistent) effects of UGC Sentiment, Volume of Post, Depth of Post, community Rating and lags of Diffusion are conducted. Next, cointegration tests are performed to see if two or more variables are cointegrated or spuriously related. In the fourth step, a Vector Autoregressive (VAR) model that is able to account for endogeneity, dynamic responses and interactions among variables is specified (Sims 1977, 1980). Fifth, short- and long-run responses of Diffusion to a shock of UGC Sentiment and Volume of Post are estimated in the form of innovations and residuals. Finally, we check the robustness of the model with tests of fixed effect and random effect. Table 6 shows a summary of the six analysis steps and their overall results.

Table 6: Summary of the six analysis steps and their overall results

Analysis Steps	Results	Support
Time-seties Tests		
Panel Unit Root	Diffusion stable; All significant except for the linear trend (Breitung)	Rating (ns)
Endogeneity Test	Sig. causality and feedbacks b/w Diffusion and other variables	Lag < 4; Lag=1 or 2
Cointegration Test	Mixed results b/w Johansen Fisher test and Pedroni & Kao test	Reject null
Model Specification		
VAR Model	Sentiment → Diffusion (one lag); Diffusion → Sentiment (two lags)	H1 supported
VEC Model	Improve Adj-R^2 (27.9% to 55%) and Akaike AIC (10.96 to 10.67)	Strong
Impulse Response GIRF		
Early Stage	Diffusion responses from 3.72 (short) to 19.2 (long-term)	H2 supported (strong)
Late Stage	Diffusion responses from 0.18 (short) to 2.01 (long-term)	Weak response
Wear in & out Shock		
Single Generation	Wear-in in 2-3rd week and wear-out in 4-7th week	H3 supported
Multi Generation	Wear-in in 2nd week one and wear-out 3th week	Weak

UNIT TEST FOR STATIONARITY

The main reason why it is important to know whether a time series is stationary or nonstationary before we can do a time-series analysis is that there is a danger of obtaining significant test results from unrelated data when nonstationary series are used in causality analysis. The outcomes are said to be spurious (Hill, Griffiths, & Lim, 2011). To avoid this, it is necessary to perform a unit root test for stationarity. In addition, this kind of tests also helps to decide how each variable should be included in the dynamic model. If the tested variable is stationary, it will be included as in levels, otherwise it would be included as in differences.

Since some time-series data of video games didn't have at least 6 data points to be stable enough as required by the SAS Enterprise program, they are eliminated[7] before the test is performed. The final panel now consists of 154 game titles. The unit root test of panel data gives a summary of both panel and individual tests. Specifically, while Levin, Lin, and Chu (2002) and Breitung (2000) methods for panel data state the null hypothesis that panel data has unit root and assume common unit root process, Im, Pesaran and Shin (2003), Augmented Dickey-Fuller (ADF) (1979), and Phillips-Perron (PP) (1988) tests for individual data state the null hypothesis that panel data has unit root (but assume individual unit root process).

The unit root tests are very consistent. The results show that all panel unit root tests excepts some of Breitung ones are significantly rejected the null hypotheses at an alpha level of 5% or lower. Diffusion or Adoption Rate (weekly) receives the most consistent result which shows a strong

[7] They will be used in another cross-sectional study

stationarity of the variable. Among others, Past Adoption at time t-1, UGC Sentiment (weekly sentiment score), Volume of Post (accumulative number of posts), and Depth of Post (average words per post) shows some sort of stationary. Their test results are significant in all tests except for the linear trend (Breitung). However, when the same linear-trend tests were taken for unit root in the first difference, the results all turn to be significant. Therefore, these variables can be considered weak stationary. Table 7 shows summaries of panel unit root tests for time-series used in the model.

Table 7: Summaries of Panel Unit Root tests for variables at level

Method \ Variables (Null: Unit Root)	**Adoption Rate**	**Past Adoption**	**UGC Sentiment**	**Volume of Post**	**Depth of Post**	**Rating**
Assumes common unit root process						
Levin, Lin & Chu t	-71.99	-54.69	-1651.12	-1674.93	-54.61	302.87
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(1.000)
Breitung t-stat	-11.88	8.39*	-0.39*	-0.18*	-16.24	24.27*
	(0.000)	(1.000)	(0.346)	(0.428)	(0.000)	(1.000)
Assumes individual unit root process						
Im, Pesaran Shin w	-71.31	-45.13	-2499.77	-2583.34	-51.60	-147.69
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ADF-Fisher Chi-sq.	3781.77	2438.83	8671.72	7937.62	2918.93	1732.28
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PP-Fisher Chi-square	4222.49	3010.79	9740.99	9674.49	3288.30	403.78
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

( ): values of probability

*: not significant

In contrast, Rating of online video games shows some presence of a unit root. That means this rating variable evolves over time. This is not a surprised result. It actually reflects the real situation in which the value of rating for next week will be determined in a way that it takes average of all previous weeks. Thus, if there was no rating this week, ratings of the games would be the same next week. Theoretically, a missing rating value should not be displayed continuously. In order for Rating to have significant unit root tests, the time-series variable has to take a second-order difference without the intercept parameter, while other variables which have an insignificant Breitung test in the previous section only need to take first-order differences to make the Breitung index significant. Table 8 shows summaries of panel unit toot tests for time-series (at first difference).

Table 8: Summaries of Panel Unit Root tests at first-order differences

Method \ Variable Null Hypothesis: Unit Root	**Past Adoption**	**UGC Sentiment**	**Volume of Post**	**Rating***
Assumes common unit root process				
Levin, Lin & Chu t	-70.43	-1239.71	-1403.16	-214.18
	(0.000)	(0.000)	(0.000)	(0.000)
Breitung t-stat	-10.88	-6.56	-8.13	N/A
	(0.000)	(0.000)	(0.000)	N/A
Assumes individual unit root process				
Im, Pesaran and Shin W-stat	-69.2999	-854.945	-801.043	-147.69
	(0.000)	(0.000)	(0.000)	(0.000)
ADF - Fisher Chi-square	3860.20	7953.39	7477.46	6128.31
	(0.000)	(0.000)	(0.000)	(0.000)
PP - Fisher Chi-square	4547.85	12539.70	12354.70	12334.60
	(0.000)	(0.000)	(0.000)	(0.000)

ENDOGENEITY TEST (GRANGER CAUSALITY)

The second step of this analysis is the Granger test which can help to specify lagged effects among variables and their dynamic relationships in the proposed model. The procedure is to test for endogeneity among UGC Sentiment (weekly sentiment score), Volume of Posts (accumulative number of posts), Depth of Post (average number of words), Rating (weekly average score by site members), and Diffusion (adoption rate of a specific online video game). This statistical test follows Clive Granger's (1969) proposal to exam the causal relationship between two variables. Note that before testing the causality between the two time series, we need to assess their stationary characteristics as shown previously.

There are a number of Granger Causality procedures. Some most popular are direct Granger procedure, Haugh-Pierce procedure, and Hsiao procedure. The first one directly derives from the Granger definition of causality. It employs a linear prediction function. To test for a simple causality between two time series from UGC Sentiment to Diffusion, we can directly regress diffusion at time t on its lagged values and UGC sentiment lagged values to see if the error variance is significantly reduced. The method uses OLS[8] to estimate parameters of the regression equation. The second method was first introduced by Haugh (1976). Then, it was extended by Haugh and Pierce (1977). In this test, the first step is to estimate the univariate ARMA models for the endogenous Y and exogenous X variables. It is then based on the cross-correlations $\rho_{ab}(k)$ between the residuals a and b of these models to test the causality. The last procedure was first

[8] Ordinary Least Square

proposed by Hsiao in 1979. It initially adds an information criterion to determine the lag lengths corresponding to the application of the direct Granger procedure. The procedure starts to estimate the optimal lag length of the univariate autoregressive process of the endogenous Y, then the optimal lag length of the explanatory variable X in the equation of Y, while fixing the lag length of Y.

Suppose that we have at least weakly stationary time series. According to Granger’s proposal, if X (UGC Sentiment) is causal to Y (Diffusion), current and lagged values of X should contain information that can be used to improve the explanation of Y. This implies that the information is not contained in the current and lagged values of Y. Granger causality of the dependent variable “Diffusion” by the independent variable “UGC Sentiment” means that we can predict Diffusion substantially better by knowing the history of UGC Sentiment than by only knowing the history of Diffusion itself. Otherwise it would be sufficient to consider only the present and past values of Diffusion (Granger, 1969).

A series of Granger causality tests are performed on each pair of the above variables. Since the current step is not only interested in whether variable X causes variable Y at a specific lag, it might also look for a full range of modeling. Thus, it uses lags up to 12 (a quarter) as a rule of thumb for a weekly event having some sort of cyclical effects. The Granger Causality tests indicate substantial endogeneity among the variables analyzed. Especially, at a level of lags < 4, all hypothesized exogenous variables show a Granger causality on Diffusion and vice versa. In contrast, when the lag level is larger than or equal to 4, except Rating (first difference), Diffusion does not cause a significant Granger on any other three variables. Only UGC Sentiment and Post

Rate (Volume of Post difference) have Grange Causality with Diffusion. Dual causalities between Diffusion and other exogenous varaibles when lags is less than 4 explain the dynamic relationships among these variables during the first 4 weeks (one month). In addition, the Granger test results also indicate some causalities of Diffusion, Volume of Post, and Depth of Post on Rating for the lags between 8 and 12. The procedure runs causality for lags up to 16 (around 4 months) and report the results for the lag that has the highest significance for Granger Causality. Table 24 shows a summary of tests for Granger Causality using Direct Granger Procedure.[9]

We can infer that during the initial stage, some active members, game advocators or pre-adopters who added a game of interest into their wish lists might start to post some comments or reviews about the game, which motivates early adopters to adopt and play the game. A number of them are also active members. They, then would come back to the game page and post what they might experience with the game. Depending on the level of accumulated sentiment, this loop will evolve more or less. Thus, there is a dual causality between Diffusion and UGC Sentiment. Note that one month is also the average time for a gamer to play and finish a game. With lags larger than 4, while UGC Sentiment and Volume of Post still show some motivation for new adopters, a number of previous adopters did not come back to post on the game page since they did not want to comment on the game that already receives a number of posts (Dellarocas et al., 2010). Thus, after a few weeks, Diffusion in the previous time period does not indicate any signal about UGC level of the next period. Therefore, we only have a cause from UGC to Diffusion during this time. In addition to 12 lags tested, the study also performs Granger Causality Tests for lags

[9] Please see Appendix for details

of 13 to 16 and found that the lags of 14 and 15 tests indicate some unstable causality, while the lag of 16 test shows no causality among variables. The extending summary of Granger tests for lags of 13 to 16 was not presented here because it does not affect our research outcome.

A previous study found that 50% adoptions occur within 4 months after a video game was released (Zhu & Zhang, 2010). The 4-month period is almost equal to 16 weeks (16 lags). This means that reciprocal effects among variables are more likely to occur in the first half diffusion process than in the second half. The result shares a common agreement with past research and gives a positive support on the idea that UGC has a dynamic relationship with diffusion in the early stage than the late stage of the diffusion process.

COINTEGRATION TEST

Basically, when two or more variables are added into a time-series model, we need to conduct the cointegration test to see whether these variables are cointegrated or spuriously related, especially for nonstationary variables, which might lead to severe problems causing least-squares regression parameters not converge towards zero. The symptom of a spurious regression means that R-square value is inflated and would be greater than Durbin Watson statistics.

The cointegration test can be done with a procedure developed by Johansen (1988) and Johansen, Mosconi, and Nielsen (2000). The procedure investigates whether evolving variables are in long-run equilibrium. For panel data, the procedure of Johansen Fisher Panel Cointegration test is applied. As shown in the section of panel unit root test, UGC Sentiment, Volume of Post, Depth of Post, and Rating are non-stationary in one of the test procedures. Thus,

the panel cointegration model will consists of these variables. Moreover, there is a precondition for running this kind of model. That is variables must be non-stationary at level. But, when they are converted into the first difference, they all then become stationary time-series.

Table 9: Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Series: Adoption Rate, UGC Sentiment, Volume of Post , Depth of Post, and Rating

Trend assumption: Linear deterministic trend (restricted)

Observations: 7491

No. of CE(s)	**Trace test***	**Prob.**	**Max-Eigen test***	**Prob.**
None	3769.	0.0000	2314.	0.0000
At most 1	3345.	0.0000	5731.	0.0000
At most 2	2295.	0.0000	1243.	0.0000
At most 3	1449.	0.0000	857.9	0.0000
At most 4	632.2	0.0000	632.2	0.0000

* All of tests are significant as its P-value < 0.05

The cointegration results show that the tests does not detect any long-term equilibrium among the evolving variables, even when the dependent variable, Diffusion, is added into the model. The Johansen Fisher Statistics values from both trace test and max-Eigen test are significant higher than Chi-square critical values in all cases of hypothesized number of cointegrations. Therefore, we can conclude that the null hypotheses are rejected and that the variables of interest are not cointegrated for the Fisher test. That means we can include these variables in the proposed model. However, Pedroni and Kao test shows a cointegration among UGC Sentiment and Volume of Post. This is also important for the interpretation of the later results. Table 9

shows test results from an unrestricted Cointegration Rank test (Trace and Maximum Eigenvalue) with an assumption of linear deterministic trend. The first column shows hypothesized number of cointegration. The next two are Fisher statistic from the Trace test and P-value of the test. The last two are Fisher statistic from the Max-Eigen test and its P-value.

MODEL SPECIFICATION

VECTOR AUTOREGRESSIVE MODEL

According to the above Johansen test, no cointegration was found among variables of interest. Thus, based on the result of the Johansen test, a VAR model can be used in this case. The VAR model describes a system of equations in which each variable is a function of its own lag and the lag of the other variables in the system. The above Granger-Causality (endogeneity), evolution (unit root) and cointegration tests provide some directions to finalize the specification of the Vector Autoregressive model (Dekimpe & Hanssens, 1999). As it turns out that there are dual causalities among variables in some points, the vector of endogenous variable, Diffusion, will be regressed on their own past and the past of the other variables (Past Adoption, Volume of Post, UGC Sentiment, Rating, and Depth of Post). Via this process, the specification will explain the behavior of each variable and allow for dynamic feedback loops such that pre-adoption induces Volume of Post, UGC Sentiment and other UGC in the intro week, which stimulates new adoptions in the next week, which in turns stimulates UGC again after another week.

Dynamic Model

Based on the Granger-Causality results, the vector of endogenous variables includes Adoption Rate (new adopters/week), UGC Sentiment (sentiment score), and Volume of Post (accumulative number of posts). The vector of exogenous variables for each endogenous variable consists of an intercept, Past Adoption (accumulative adopters), Square of Past Adoption (accumulative adopters^2), UGC Sentiment, Volume of Post, Depth of Post (average number of words per post),

Rating[10] (community score), and others. Before a full VAR model is analyzed, it is necessary to conduct a buffer step in which we can exam a partial VAR model which only includes Diffusion and UGC Sentiment. Since the Granger tests show dual causalities between them for the lags less than 4 and optimal at 2, the parameter for the lag intervals of endogenous variables will be 1 to 2. To analyze the reciprocal effects between Diffusion and UGC Sentiment, we perform two VAR models. In the first one, Diffusion is modeled to depend on UGC Sentiment and its one and two lags. Note that by nature, the level and square of past adoption variables are added into the model. In the second model, UGC Sentiment is assigned as the endogenous variable, whereas Diffusion as the exogenous variable. By default, the one and two lags of both UGC Sentiment and Diffusion are added into the model.

On one hand, the result from model 1 shows that there are lag effects on both Diffusion and UGC Sentiment. Specifically, UGC Sentiment positively stimulates instant adoption, after one week and after two weeks. Likewise, Diffusion (adoption rate) can impact on UGC Sentiment in the same week or after two weeks. This is consistent with previous studies which propose lag effects of online word of mouth on a retail's online store traffic (Stacey, Pauwels, & Lackman, 2013). The Wald test clearly confirms that the past of UGC Sentiment (one lag) causes dynamic effects on Diffusion at the presence of Diffusion lags itself. However, a further analysis shows that the two-lag Sentiment does not has a significant impact. The level and square of past adoptions, respectively, have significantly positive and negative effects on Diffusion, which are very consistent with the theoretical Bass model. The Adj. R-squared value in this case is 0.278 and Akaike AIC is 10.96.

[10] Difference of Rating is used in the model instead of Rating level as a result of the Granger test.

Table 10: Dynamic Model of Diffusion (Adoption Rate) and UGC Sentiment

DV = Diffusion	**Model 1**	**DV = Sentiment**	**Model 2**
Past Adoption Y_{t-1}	0.0164		
Past Adoption Y_{t-1}^2	-9.29E-07		
UGC Sentiment	1.617	Diffusion	0.0025
One-lag UGC Sentiment	0.697	One-lag Diffusion	5.02E-05*
Two-lag UGC Sentiment	-0.047*	Two-lag Diffusion	0.0015
One-lag Diffusion	0.151	One-lag UGC Sentiment	0.044
Two-lag Diffusion	0.188	Two-lag UGC Sentiment	0.012
Adj-R^2	0.278	Adj-R^2	0.204
Akaike AIC	10.96	Akaike AIC	4.71
Observations	7183	Observations	7183

* Not significant

On the other hand, Diffusion shows some weak effects on UGC Sentiment, reflecting some consistency with the previous causality tests. The Wald test shows that the pasts of Diffusion did jointly cause some effects on UGC Sentiment at the presence of Sentiment lags, but these effects are weak. That is the two-lag Diffusion has a strongly positive effect on UGC Sentiment, whereas the one-lag Diffusion does not. UGC Sentiment have positive relationships with its one and two lags. Some previous studies also confirm the positive signs when they exam the relationship among past reviews and current reviews (Dellarocas et al., 2010; Moe & Trusov,

2011). The results are consistent in a way that the content of current reviews is clearly influenced by that of past reviews in a short term effect. So, the sign should be positive. For a long-term impact, this might not hold as shown in the Granger causality section. That's why we only look at one lag (reviews last week vs. this week) or two lags (reviews last two weeks). Table 10 shows analysis results for the VAR model with Diffusion and UGC Sentiment. The Adj. R-squared value of model 2 is 0.204 and Akaike AIC is 4.71. Although model 2 has a better Akaike AIC value, its explanatory power is much lower than that of model 1. Therefore, we can conclude that a reciprocal relationship has occurred between Diffusion and UGC Sentiment. However, the causality from UGC Sentiment to Diffusion is much stronger than that from Diffusion to UGC Sentiment.

Full Model

To estimate the VAR model, we first apply two lags to reach a balance of an acceptable forecasting power and modeling parsimony for an initial model. Besides, from the Granger-Causality test, majority of variables of interest have their highest significance of F-statistics for one or two lags. The procedure to specify the VAR model step by step adds exogenous variables for one or two lags into the VAR model. Following the theory of new product diffusion, the level and square of Past Adoption at t-1 are always added into the VAR model. Table 11 shows parameters of the estimated VAR model.

The results indicate that UGC Sentiment and Volume of Post have some sort of effects on Diffusion, while Depth of Post and Rating are not significant as explanatory factors of Diffusion. Specifically, model 1 shows that only UGC Sentiment and its one lag have a positive relationship

with diffusion. Like the dynamic model in the previous section, model 1 implies that UGC Sentiment can instantly stimulate people's adoption behavior. It also causes a one-week delay effect on the adoption rate. In contrast to model 1, model 3 points out that Volume of Post is the sole UGC metric to explain Diffusion. Besides, among UGC metrics, Volume of Post and its one and two lags indicate the strongest impact on Diffusion as their coefficients have the highest t-value except that of Past Adoption. This finding is consistent with past research regarding the relationship between Volume of Post and Business Performance (Tirunillai & Tellis, 2012).

Table 11: Estimated Parameters of Full VAR Models

DV = Diffusion	**Model 1**	**Model 2**	**Model 3**
Past Adoption Y_{t-1}	0.0164	0.0164	0.0164
Past Adoption Y_{t-1}^2	-9.29E-07	-9.26E-07	-9.26E-07
UGC Sentiment	1.617	1.559	
One-lag UGC Sentiment	0.697	0.749	
Two-lag UGC Sentiment	-0.047*	0.582	
Volume of Post			1.237
One-lag Volume of Post			0.406
Two-lag Volume of Post		-0.398	-0.033
Adj-R^2	0.278	0.279	0.279
Akaike AIC	10.96	10.96	10.96
Observations	7183	7183	7183

Model 2 shares a common outcome with model 1 in terms of the positive relationship between UGC Sentiment and Diffusion. However, results from the model 2 show that both two-lag UGC Sentiment and two-lag Volume of Post are significant to influence people's adoption behavior. While UGC Sentiment still has some positive impact after a two-week delay, Volume of Post causes a negative rather than a positive effect. Although it seems to cause a conflict between UGC Sentiment and Volume of Post, the result reflects an agreement with past findings. If a review had some good sentiment content, it would receive helpfulness and thus stimulate adoption behavior. At the same time, people prefer to post reviews for products that are less available and less successful in the market (Dellarocas et al., 2010).

In all three models, the finding is consistent in a way that Diffusion at time t is strongly dependent on the level and square of Past Adoption at time t-1. It also shows a strong consistency with the theory of diffusion as the VAR model becomes significantly stronger when the level and square of Past Adoption at t-1 are added in the model. Actually, the largest variance of Diffusion (Adoption Rate) can be explained by Past Adoption because they are directly related to adoption behavior of OSN users. The values of Akaike Information Criterion which reflects the parsimony of a model are comparable among the three models. However, the Adj. R-squared values of model 2 and 3 are slightly better than that of model 1. In practice, we can use all three model to explain the variance of Diffusion because their modeling indices are not much different and both Volume of Post and UGC Sentiment can be converted to a very good explanatory power for Diffusion (adoption rate).

Table 12: Wald Test of Volume of Post and UGC Sentiment joint effects on Diffusion

Wald Test:

Test Statistic	Value	df	Probability
Chi-square	182.233	2	0.0000

Null Hypothesis: C(1)=C(2)=0

Normalized Restriction (= 0)	Value	Std. Err.
C(1) Volume of Post	0.464	0.0363
C(2) UGC Sentiment	0.038	0.0128

The Wald test clearly confirms that UGC Sentiment and Volume of Post jointly cause effects on Diffusion at the presence of Diffusion lags itself. The F-statistic is significant to reject the null hypothesis. That means the coefficients of these sentiment variables are significantly different from zero. Likewise, the coefficients of Volume of Post and its one and two lags are also significant in another Wald test. Therefore, we conclude that both UGC Sentiment and Volume of Post significantly contribute to explain the variance of Diffusion. The contributions can be instantly or delayed by one or two weeks. However, they cannot be in the same model because they are cointegrated. Table 12 displays the result of the Wald test of Volume of Post and UGC Sentiment effecting on Diffusion.

VECTOR ERROR CORRECTION MODEL

Unlike the outcome of the Johansen test, the result of the Pedroni and Kao cointegration test shows that there are cointegrations among variables. And in some panel unit root tests, some variables do not contain a linear deterministic trend. Thus, a VEC can be used in this case. Actually, a VEC model is a special form of the VAR for I(1)[11] variables that are cointegrated. In this estimation, we first assume there is a cointegration between Diffusion and either Volume of Post or UGC Sentiment that is the number of coitegration (rank) is one. Then, cointegrations between Diffusion and both Volume of Post and UGC Sentiment are taken into account. That means that the number of coitegration (rank) is two.

One-Rank Cointegration

In the VEC model 4 with an assumed cointegration between Diffusion and UGC Sentiment, the results with no trend in data show that both the difference of UGC Sentiment (one and two lags) and the level of Volume of Post (one and two lags) have a significant relationship with the difference of Diffusion in the presence of the second order of one-lag Diffusion. When we estimate the VEC model with either a linear trend in data or a quadratic trend in data, both the difference of UGC Sentiment (one and two lags) and the level of Volume of Post (one and two lags) still indicate a significant impact on the difference of Diffusion. Moreover, the modeling indices of Adj. R-square and Akaike AIC are improved and have the values of 0.54 (10.69) and 0.55 (10.67)[12]. Table 13 shows results of the VEC Model with one-rank cointegration.

[11] Integrated of order one

[12] The quadratic model does not significantly improve over the linear model.

Table 13: VEC Model 4 with a Cointegration between Diffusion and UGC Sentiment

DV = D(Diffusion)	**No Trend**	**Linear Trend**
One lag Δ(Diffusion)	-0.381	-0.341
	[-35.65]	[-31.00]
Two lag Δ(Diffusion)	-0.161	-0.145
	[-19.82]	[-17.96]
Past Adoption$_{t-1}$	0.0141	0.0135
	[11.15]	[12.61]
Past Adoption$_{t-1}^{2}$	-8.35E-07	-6.72E-07
	[-6.83]	[-5.18]
One lag Δ(UGC Sentiment)	-1.481	-1.458
	[-2.84]	[-2.82]
Two lag Δ(UGC Sentiment)	-0.035	-0.041
	[-3.04]	[-3.64]
One lag Volume of Post)	-2.571	-2.223
	[-6.33]	[-5.51]
Two lag Volume of Post	-0.901	-0.880
	[-2.80]	[-2.76]
Adj. R-squared	0.539	0.550
Akaike AIC	10.694	10.671
Schwarz SC	10.702	10.681
Observations	7029	7029

In the VEC model 5 with one cointegration rank for Volume of Post, when no trend in data is chosen, the results show that both the difference of Volume of Post and the level of UGC

Sentiment have a significant relationship with the difference of Diffusion in the presence of the one and two-lag Diffusions.

Table 14: VEC Model 5 with A Cointegration between Diffusion and Volume of Post

DV = D(Diffusion)	**No Trend**	**Linear Trend**
One lag Δ(Diffusion)	-0.381	-0.341
	[-35.65]	[-31.00]
Two lag Δ(Diffusion)	-0.161	-0.145
	[-19.82]	[-17.96]
Past Adoption_{t-1}	0.0141	0.0135
	[11.15]	[12.61]
Past Adoption_{t-1}^2	-8.35E-07	-6.72E-07
	[-6.83]	[-5.18]
One lag UGC Sentiment	-3.136	-1.397
	[-2.82]	[-3.02]
Two lag UGC Sentiment	-4.065	-2.809
	[-2.04]	[-2.41]
One lag Δ(Volume of Post)	-1.704	-1.688
	[-4.71]	[-5.13]
Two lag Δ(Volume of Post)	-0.009	-0.016
	[-2.23]	[-2.65]
Adj. R-squared	0.532	0.540
Akaike AIC	10.704	10.681
Schwarz SC	10.715	10.693
Observations	7029	7029

When a linear trend in data in CE[13] is assumed, we have a similar results. But, both Adj. R-square and Akaike AIC indices are slight improved from 0.53 (10.69) to 0.54 (10.68). Table 14 shows results of the VEC Model with a cointegration between Diffusion and Volume of Post.

Note that when the quadratic trend in data is considered, the VEC model is slightly improved. The explained variation of the difference of Diffusion is almost the same and the Adj. R-square increase with a small amount from 0.53 to 0.54.

Multi-Rank Cointegration

In the VEC model 6 with multiple cointegrations (rank more than two) among Diffusion and Volume of Post and UGC Sentiment, the results show that both differences of Volume of Post (one lag) and UGC Sentiment (one lag) are significant predictors of the Diffusion difference when we assume no linear trend in data and in the presence of the differences of Diffusion (one and two lags) and the second order of Diffusion at time t-1. However, compared with previous models, the model performs is not good. Its indices significantly decrease from 0.550 to 0.402 for Adj. R-square and from 10.67 to 10.95 for Akaike AIC. When linear and quadratic trends in data are taken into account, the results are similar and the performance of the VEC model is not significantly improved. Specifically, both differences of Volume of Post (one lag) and UGC Sentiment (one lag) are significant predictors of the Diffusion difference. The model indices are 0.402 and 0.402 for Adj. R-square and 10.957 and 10.957 for Akaike AIC. Table 15 shows the VEC Model with cointegrations among Diffusion, Volume of Post and UGC Sentiment.

[13] CE: Cointegration equation

Table 15: VEC Model 6 with Two-rank Cointegrations

DV = D(Diffusion)	**No Trend**	**Linear Trend**
One lag Δ(Diffusion)	-0.381	-0.341
	[-35.65]	[-31.00]
Two lag Δ(Diffusion)	-0.161	-0.145
	[-19.82]	[-17.96]
Past Adoption$_{t-1}$	0.0141	-0.006
	[11.15]	[12.61]
Past Adoption$_{t-1}^2$	-8.35E-07	5.12E-07
	[-6.83]	[-4.55]
One lag Δ(UGC Sentiment)	-1.590	-1.098
	[-2.66]	[-2.82]
Two lag Δ(UGC Sentiment)	0.021	-0.042
	[0.096]	[-0.115]
One lag Δ(Volume of Post)	1.160	0.856
	[3.15]	[3.20]
Two lag Δ(Volume of Post)	-0.004	0.028
	[-0.031]	[0.057]
Adj. R-squared	0.402	0.402
Akaike AIC	10.957	10.957
Schwarz SC	10.966	10.966
Observations	7029	7029

A combination of all VEC results indicates that the VEC models considering a linear trend in data, in general, perform better than those VEC models with an assumption of no trend in data. In all three models, Diffusion is strongly dependent on the level and square of Past Adoption.

Table 16: Estimated Parameters of VEC Models with Linear Trend in Data

DV = Δ Diffusion	**Model 4**	**Model 5**	**Model 6**
Past Adoption Y_{t-1}	0.0135	0.0135	-0.006
Past Adoption Y_{t-1}^2	-6.29E-07	-6.77E-07	5.12E-07
One-lag Δ UGC Sentiment	-1.45	-1.397	-1.098
Two-lag Δ UGC Sentiment	-0.04	-2.809	-0.042*
One-lag Δ Volume of Post	-2.22	-1.688	0.856
Two-lag Δ Volume of Post	-0.88	-0.016	0.028*
Adj-R^2	0.55	0.54	0.40
Akaike AIC	10.67	10.68	10.95
Observations	7029	7029	7029

The results also indicate that Volume of Post and UGC Sentiment have significant impacts on Diffusion, whereas Depth of Post and Rating are not significant enough to explain the variance of Diffusion. Among significant VEC models, model 4 has the highest Adj-R square and the lowest Akaike AIC values. Thus, model 4 is considered the best one to explain dynamic patterns of Diffusion. Moreover, the adjusted R-square value is significantly improved from 0.279 (model 2) to 0.55 (model 4). This means that when we use a VEC approach to correct cointegrations among time-series variables, the proposed model performs much better and is able to explain more than half of the Diffusion variance.

Fixed Effects vs Random Effects

By nature, video games are products with a wide range of features varying in terms of genre, platform, multi-generation, structure, rules etc. Besides the above analyses of the main effects, we may also be interested in whether the model can be generalized on different levels of the variables of interest and other grouping variables. Panel data can help us to learn more about fixed effects and random effects on different levels of the variables.

Fixed Effects

The fixed effects model allows for different intercepts for each individual. The implication of fixed effect is due to the fact that although intercepts may differ across video games, the intercept may not vary over time. That is it is time invariant. With pooled equation estimation (Ordinary least square OLS), the panel nature of the data is ignored, and the error is assumed to have constant variance and to be uncorrelated over time and individuals. In some cases, we can run a pooled least squares model before estimating the parameters of the fixed effects model.

The fixed effects estimator is used here to subtract out the intercepts prior to estimation. The results of the fixed effects model show that coefficients of predictors are similar to that of the pooled model. However, while the coefficient of Volume of Post is still significant, the coefficient of UGC Sentiment is not at the alpha level of 5%. Table 17 shows the estimated results of the fixed model. Note that we use a short way to transform all time-series into deviation using the cross-section fixed (dummy variables) approach.

Table 17: Estimated results of the fixed effect model for Diffusion

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	18.96066	0.814988	23.26496	0.0000
One-lag Diffusion	0.049877	0.011310	4.410163	0.0000
Two-lag Diffusion	0.118169	0.009069	13.02938	0.0000
One-lag Volume of Post	0.433733	0.034482	12.57869	0.0000
Two-lag UGC Sentiment	-0.018924	0.012131	-1.560062	0.1188
Past $\text{Adoption}_{t-1}^{2}$	-1.84E-06	1.12E-07	-16.36072	0.0000

Effects Specification*

R-squared	0.356120	Mean dependent var.	17.30499
Adjusted R-squared	0.341637	S.D. dependent var.	68.30536
S.E. of regression	55.42269	Akaike info criterion	10.88974
Sum squared residual	21575441	Schwarz criterion	11.04202
Log likelihood	-38951.51	Hannan-Quinn criterion	10.94215
F-statistic	24.58779	Durbin-Watson stat	1.937471
Prob (F-statistic)	0.000000		

* Cross-section fixed (dummy variables)

The meaning of such a fixed effect assumes that the intercept would capture all behavioral differences between video games, referred to as individual heterogeneity. We include individual intercepts into the model to “control” for video game-specific, time-invariant characteristics. Thus, the model with these features is called a fixed effects model for our panel data on diffusion. The intercepts are called fixed effects for video game characteristics (Hill et al., 2011).

If we turn to the standard errors, t-values, and p-values, we find that the inference for UGC Sentiment is not relevant because it is not sensitive to whether or not the fixed effects are included into the model. Both t-value and p-value of the variable did not show a significant effect. When we look at F-statistic and P-value of the whole model, we also find that the fixed effects model is significant. That means there is at least one exogenous variable or one characteristic of video games creating individual heterogeneity. In addition, the adjusted R square of the fixed effects model is 34%, higher than that of the VAR model, but lower than that of the VEC model. This suggests that some within-individual error correlation among video games still remains after including the fixed effects.

Random Effects

In the random effects model, we continue to assume that individual differences are captured by difference in the intercept parameter, but it is different that the individual games in the sample were randomly selected, and we treat the individual differences as random rather than fixed. The results of the random effects model is similar to that of the pooled model, but is different from that of the fixed model. Both the coefficients of the predictors, Volume of Post and UGC Sentiment are significant. However, their explanatory powers are weak as the adj. R-square only increases by 2% when they are added into the model. Both weighted and unweighted models are indifferent as they have the same adj. R-square. Table 18 shows the estimated results of the random effects model.

Table 18: Estimated results of the random effects model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Intercept	5.903854	0.691502	8.537726	0.0000
One-lag Diffusion	0.184530	0.010530	17.52358	0.0000
Two-lag Diffusion	0.215687	0.008494	25.39349	0.0000
One-lag Volume of Post	0.463995	0.034152	13.58623	0.0000
Two-lag UGC Sentiment	-0.038581	0.012040	-3.204513	0.0014
Past $\text{Adoption}_{t-1}{}^2$	9.26E-07	5.71E-08	16.23246	0.0000
	Effects	Specification		
			S.D.	Rho
Cross-section random			0.000000	0.0000
Idiosyncratic random			55.42269	1.0000
		Weighted Statistics		
R-squared	0.257267	Mean dependent var.		17.30499
Adjusted R-squared	0.256749	S.D. dependent var.		68.30536
S.E. of regression	58.88740	Sum squared resid.		24887871
F-statistic	497.1919	Durbin-Watson stat.		2.028039
Prob. (F-statistic)	0.000000			
		Unweighted Statistics		
R-squared	0.257267	Mean dependent var.		17.30499
Sum squared residual	24887871	Durbin-Watson stat.		2.028039

Model Comparison

Which one is the appropriate model to accept? To answer this, we should rum the Hausman Test. The null hypothesis states that the random effect model is an alternative of the fixed effects model, while the alternative hypothesis states the opposite. The Hausman test significantly rejects the null hypothesis. Therefore, the variation within and between individual games does not distinct. Table 19 shows a comparison between fixed effects and random effects.

The Hausman test compares the coefficient estimates from the fixed effects model to those from the random effects model. Theoretically, the random effects model is able to take into account of variation between video games as well as variation within video games which is the variation among gamers who adopt the same game. This ability makes the random effects model more attractive than the fixed effects model. In order for the random effects estimator to be unbiased in such a large sample as in the current study, the assumption that the effects have to be uncorrelated with the exogenous variables must hold.

The Hausman test uses Chi-square statistic to check if there is a significant diverge between the random effects estimates and the fixed effects estimates. The test result indicates that Chi-square statistics is significant and there is evidence to reject null hypothesis. That means correlation between random effects and the exogenous variables significantly exists. The assumption does not hold. As pointed out in the econometric literature, random effects hardly stand with a large sample size (Hill et al., 2011). In order to make more sense about the test, we need to look closer to the comparison between fixed effects coefficients and random effects coefficients.

Table 19: Hausman Test for a Comparison between Fixed Effects and Random Effects

Correlated Random Effects - Hausman Test

Test cross-section random effects

Test Summary	**Chi-Sq. Statistic**	**Chi-Sq. d.f.**	**Prob.**
Cross-section random	1072.044	5	0.0000

Cross-section random effects test comparisons:

Variable	**Fixed**	**Random**	**Var(Diff.)**	**Prob.**
One-lag Diffusion	0.049877	0.184530	0.000017	0.0000
Two-lag Diffusion	0.118169	0.215687	0.000010	0.0000
One-lag Volume of Post	0.433733	0.463995	0.000023	0.0000
Two-lag UGC Sentiment	-0.018924	-0.038581	0.000002	0.0000
Past Adoption_{t-1}^2	-0.000002	0.000001	0.000000	0.0000

Table 19 illustrates that the chi-square at the degree of freedom of five is significant and that the different values of variance are very small although p-values are significant for all exogenous variables. Only coefficients of one and two-lag Diffusions in the fixed-effects model have somewhat big differences from those in the random-effects model . Therefore, the Hausman test shows a significant divergence between the two models, but the divergence is also bias due to our large size of a panel sample.

SHORT VS LONGTERM IMPACT (IMPULSE RESPONSE)

To analyze the impact of Volume of Post and Sentiment variables on Diffusion in short- and long-term effects, the study applies the estimated VEC model through simulations of the generalized impulse response function (Pesaran & Shin, 1998). The generalized impulse response function (GIRF) uses the VEC estimates to trace the effect of a unit shock (one standard deviation) in one of the two UGC variables (i.e. Volume of Post and UGC Sentiment) on Diffusion variable in the system over subsequent periods.

GIRF of Early Stage

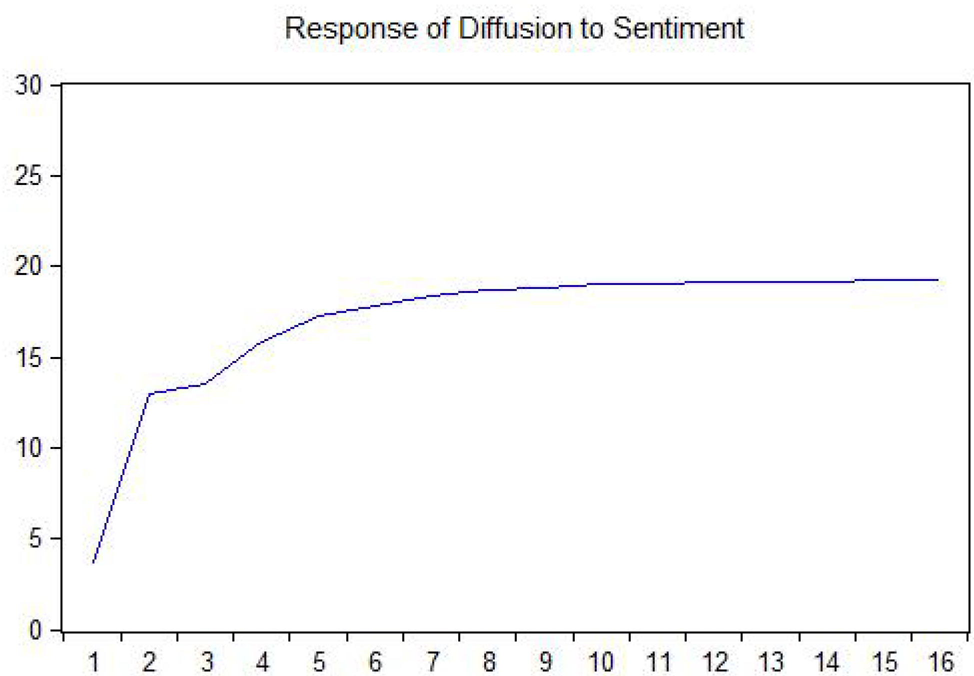

Figure 3: GIRF of Diffusion to shocks of UGC Sentiment for the early stage

The short-term impact is defined as the effect derived from estimates of the VEC model for a period of the first two weeks, the optimal lag time for the effect of UGC variables, after the shock. The long-term or cumulative impact is defined as the accumulated value of the impulse response function to reach its asymptote. Most of the accumulated effect on Diffusion reaches the long-run (Asymptotic) levels within 16 weeks. Figure 3 illustrates GIRF of Diffusion to shocks in UGC Sentiment for the early stage.

Figure 3 demonstrates that Diffusion immediately responds to a shock of UGC Sentiment at the first week. The horizontal axis has a unit of the number of weeks, while the vertical axis takes a unit of the number of basis points. The effect needs only one week to reach its peak in the second week and remains significantly different from zero for approximately four weeks. The response dramatically reduces after the first four weeks and becomes almost zero at the week sixteenth.

GIRF for Late Stage

As defined previously, the late stage of the diffusion process consists of the second half adopters who slowly adopt the new product. To analyze the response of Diffusion to a shock of UGC changes in the late stage, we apply a filter to select those adoptions occur in the second half of the diffusion curve. We then observe all responses of Diffusion and compare them with the responses in the early stage discussed in the above section. Figure 4 illustrates GIRF of Diffusion to a shock of UGC Sentiment for the later stage.

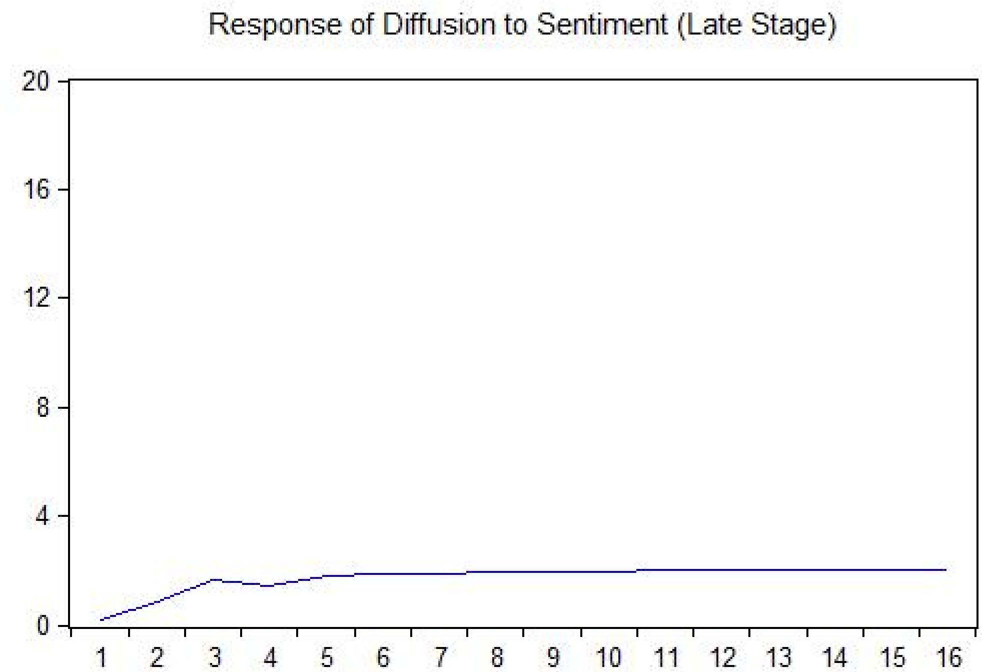

Figure 4: GIRF of Diffusion to shocks of UGC Sentiment for the early stage

Figure 4 shows that Diffusion weakly responses to a shock of UGC Sentiment. The effect needs two weeks to make a response. However, the response is not clear and not significantly different from zero. The max response only reaches 2.68 basis points, whereas the max response of Diffusion in the early stage can be up to almost 20 basis points. The effect becomes saturation after four weeks.

Table 20 presents the results of the short- and long-term impact of UGC variables on Diffusion. From the table, consistent to the diffusion theory, past Diffusion has the strongest impact on Diffusion itself during the first two weeks of the shock. However, after that the magnificence reduces and is much smaller than that of UGC Sentiment and Volume of Post.

Table 20: Short- and Long-term Impact of UGC on Diffusion

		UGC Sentiment	**Volume of Post**	**Past Adoption**
Early Stage	Short-term (1st week)	3.72	5.96	50.22
	Short-term (2nd week)	12.97	4.87	3.76
	Long-term (16th week)	19.20	10.13	3.37
Late Stage	Short-term (1st week)	0.18	0.46	24.57
	Short-term (2nd week)	0.81	1.25	1.60
	Long-term (16th week)	2.01	2.68	0.19

Unlike in the late stage, both UGC Sentiment and Volume of Post in the early stage induce a higher short-term response and a longer carryover effect for almost 16 weeks. In the early stage, a shock of Past Adoption causes the highest response of Diffusion, reaching 50 basis points in the first week. However, this response dramatically drops to less than 4 basis points after just first week. In contrast, shocks caused by UGC Sentiment and Volume of Post have a slow start at 3.72 and 5.96, respectively, in the first week. Then, they grow up significantly in the second week and reach a saturated level of 19.20 for UGC Sentiment and 10.13 for Volume of Post. In the late stage, only Past Adoption is able to cause a significant shock at 24.57 basis points in the first week. Both shocks caused by UGC Sentiment and Volume of Post are not significant. The result supports the second hypothesis which states that UGC Sentiment could cause stronger responses of diffusion in the early stage, but become less impulse in the later stage of the diffusion process.

DURATION OF IMPACT (WEAR IN & OUT SHOCK)

Single-Generation Product

Figure 5 tells us about the Accumulated Impulse Response Functions (AIRF) of Diffusion under a shock of UGC Sentiment for a single-generation product. The vertical axis illustrates the number of basis points, while the horizontal axis demonstrates time (week) the AIRF response can last. The magnificence of the response starts at a level of four basis points in the first week. Then, it substantially increases up to more than ten basis points in the fourth week.

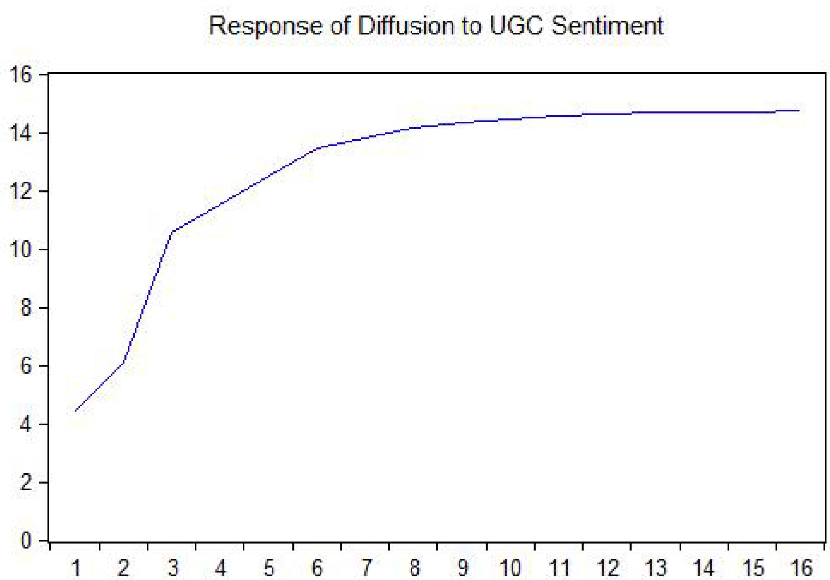

Figure 5: AIRF of Diffusion for a Single-Generation Product

Figure 6 displays a relative AIRF of UGC Sentiment on Diffusion for a single-generation product. The figure indicates that a one-standard-deviation shock in UGC Sentiment causes a substantial impact on Diffusion. The Diffusion has a wear-in at its peak in the third week. It then wears out over the fourth to seventh week before reaching a long-term equilibrium.

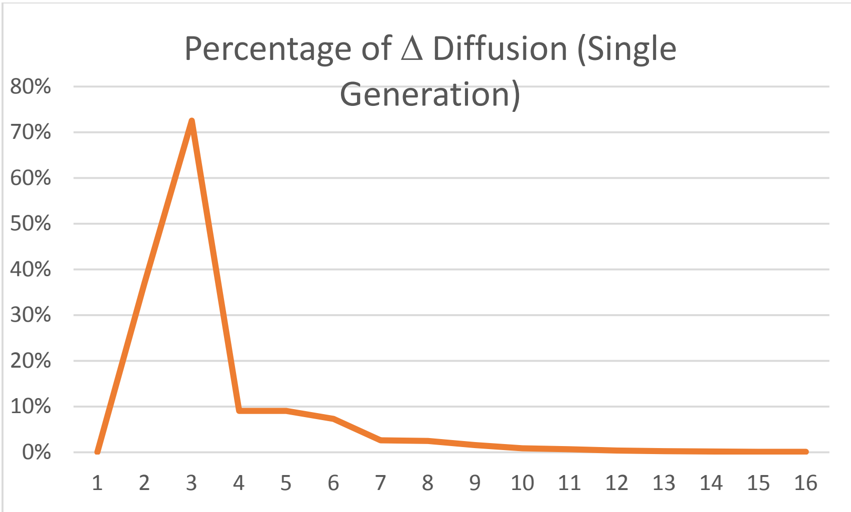

Figure 6: Relative AIRF of Diffusion for a Single-Generation Product

Multiple-Generation Product

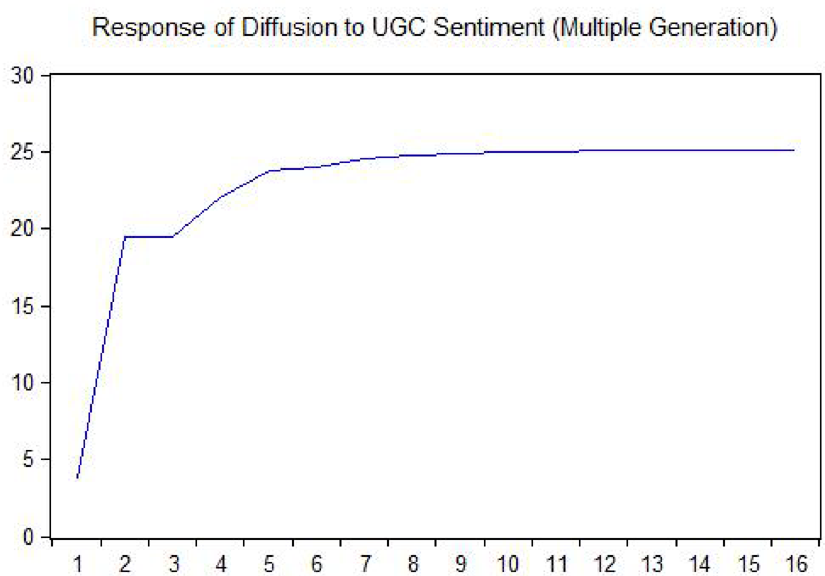

Figure 7: AIRF of Diffusion for a Multiple-Generation Product

Figure 8 displays a relative AIRF of UGC Sentiment on Diffusion for a multiple-generation product. The figure indicates that a one-standard-deviation shock in UGC Sentiment causes a

substantial impact on Diffusion. The Diffusion has a wear-in at its peak in the second week. It then wears out over the third week before reaching a long-term equilibrium.

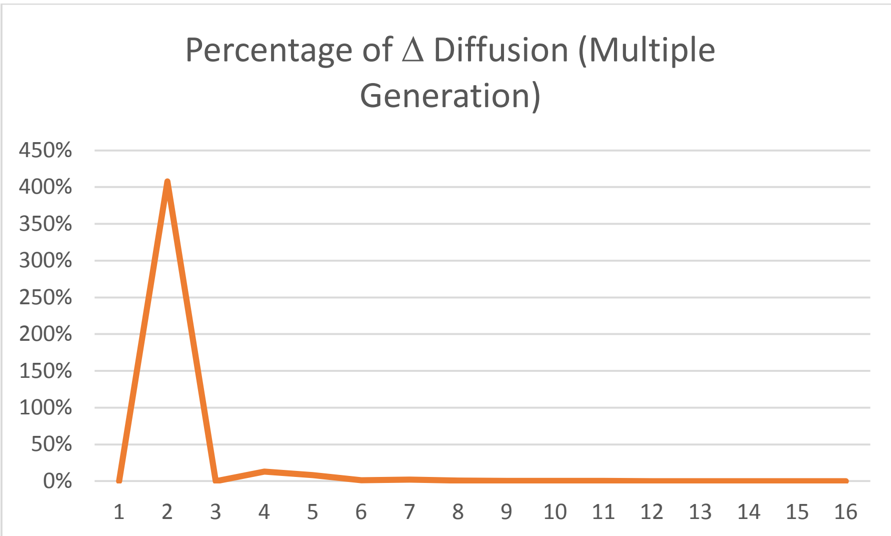

Figure 8: Relative AIRF of Diffusion for a Multiple-Generation Product

A comparison applied for the impact of UGC Sentiment on Diffusion between a single-generation product and a multiple-generation product indicates that a UGC shock of a multiple-generation product creates a higher scale of Diffusion response up to four hundred percentages, which is much higher than that of a single-generation product (around only 70%). The reason is that the multiple-generation product, in general, has a larger base of existing adopters. In contrast, the UGC shock of a single-generation product makes a slower, but much longer response of Diffusion. This implies that the shock of UGC Sentiment can last longer for a single-generation product than for a multiple-generation product. Therefore, the third hypothesis is supported.

CONCLUSION

This study is focusing on diffusion and adoption of digital artifacts. The goal is to explore the social role of user-generated content during the diffusion process of digital artifacts in the context of online social networks. The study spans a wide range of analytics methods and tools such as predictive modeling, latent sentiment analysis, data retrieval, and other tools for network analysis and visualization.

Data collection is conducted on around 260 digital products and more than 105 thousand social network nodes. The panel data for analysis is generated using a query of three different data sets. The first one includes individual information of gamers' adoption behavior. The second provides detailed information about all video games published by the selected website. The last one consists of all reviews and discussions regarding the studied video games. The combination yields a complete data set of 7,491 records for the time frame between January 2012 and October 2013[14].

Results of the study provide a deeper insight into the influence of user-generated content (UGC) on IT diffusion and how such a web system (e.g.: online social networks) can help firms enable a process of value co-creation. The study sheds light on the crowding power and the long-tail effect in online social networks. Findings also offer valuable implications for organizations to set up their strategic vision in terms of targeted marketing, customer relationship management, and information dissemination. The overall finding shows that amount of discussions (Volume of

[14] In some cases, missing data may cause a slightly different time frame.

Post) and their valence (UGC Sentiment) toward a new digital product have a dynamic impact on diffusion of the digital product. But, the relationships depend on certain situations.

Specifically, we do find dynamic relationships between Diffusion and UGC metrics including UGC Sentiment and Volume of Post. Consistent to previous studies, among UGC metrics, Volume of Post is the strongest predictor of Diffusion, so does the Business Performance. Although past research has discussed the relationship between UGC Sentiment and Business Performance, the current study is the first one to look insight the dynamic relationship between Diffusion and UGC Sentiment. UGC Sentiment has a positive and dynamic relationship with Diffusion (Adoption Rate).

Moreover, both UGC Sentiment and Volume of Post were found to induce a higher short-term response and a longer carryover effect on Diffusion in the early stage than in the late stage. In addition, we also find that a response of Diffusion to a shock of UGC Sentiment can last longer for a single-generation product than for a multiple-generation product.

Unlike previous studies, however, our study did not confirm significant impacts of information richness (Depth of Post) and game rating (Rating) on Diffusion, although Granger tests show moderate causalities among them.

CONTRIBUTIONS

Our research offers several potential contributions for advancing knowledge and understanding of the diffusion literature and user-generated-content effects. First, to the best of our knowledge, the study is the first one to claim a dynamic relationship between UGC sentiment and new product diffusion. By tracking of the number of new adopters over time and quantifying textual sentiment, our work provides a new method to collect a measurable link between UGC activities and adoption behavior. Second, the classic diffusion model is extended to include UGC terms reflecting social influences of innovators toward potential followers via online textual communication. Third, this study makes a methodological contribution by demonstrating a systematic sampling approach to collect an unbiased sample. We also show a technique to aggregate true diffusion by counting the number of new adopters over time instead of using the number of units adopted. Fourth, unlike past research which assumes a constant role of UGC during the diffusion process and among various product generations, this study indicates that the contagious role of UGC is much more important during the early stage of diffusion, especially for a brand new product rather than an extension of an existing product.

In addition, our investigation of UGC dynamic effects on new product diffusion can help managers to gain practical benefits in some ways. First, sentiment aggregation can play as a proxy to predict a new product success. Managers can apply techniques in our study to have better measures of UGC metrics, especially sentiment scores. The strong link between sentiment scores and adoption rate of a new product can help to predict if the new product is successful during the early stage. Besides, managers can also apply the proposed model to forecast sales and demand because, as pointed out in the empirical analysis section, the proposed model has a

very good fit and can explain more than 50% variance of diffusion. Moreover, when combining with spatial data of UGC metrics, managers can cluster new product demand of different markets and thus are able to control their inventory and manage their supply chain systems.

Second, our findings bring some implications for niche products and start-up companies. As pointed out, UGC carryover effects on a single-generation product last longer than on a multiple-generation product. Many niche products, especially those in the video game industry, are only launched via an online channel. Moreover, because information about niche products is not always available, an increasing of extreme reviews can be detrimental for the products. Thus, it induces a great incentive for niche product managers to monitor UGC closely. A similar situation occurs for start-up firms which primarily rely on online social networks as a low-cost channel to market their new products.

Finally, our research may help firms manage their customer relationships. An increasing number of firms have offered beneficial and/or financial incentives to existing OSN members (customers) to provide helpful new product reviews. Traditionally, customer lifetime value (CLV) or member lifetime value (MLV) is the most important metric for managers to implement a strategic move targeting on different groups of customers. CLV describes the amount of revenue or profit a member (customer) generates over her or his entire lifetime. With a new approach to track UGC, managers can add customers' UGC contributions into the firm's CLV portfolio. By that way, firms are able to maintain customers' loyalty and motivate them to participate in disseminating new product information.

Limitations

Along with academic and practical contributions, we also acknowledge several limitations in the study. First, we collect data from only one video game networking site, but not other comparable sites. Thus, data limitation prevents us from generalizing the results to different product categories. Second, UGC metrics and reviews collected could be manipulated by the site owner. Since the data collection is conducted in one website, it is hard to validate if the data are reliable or not. Third, we use SAS software to conduct sentiment analysis of new product discussions. The software is designed to analyze unrelated messages. However, a number of reviews and discussions used in the study are linked to each other. Thus, sentiment scores could be bias due to this problem. Finally, our model does not include interaction terms between UGC metrics and past adoption as suggested in the literature. This can reduce the power of the tested model to explain variance of diffusion.

Future Research

This work could be extended in several directions. First, due to data source limitation, we could not gather data of diffusion breadth and diffusion depth. Further research could explore the relationship between the three diffusion dimensions and UGC metrics. Second, most of past studies use historical data to forecast sales and demand of a new product. Future research could develop a new model of real-time forecasting based on spatial UGC metrics in different social media networking sites. Third, social influences between following hubs and innovative hubs on diffusion are different in each stage of the diffusion process (Susarla et al., 2012). Little has been

known about how these hubs use UGC to influence on their followers' adoption behavior. Finally, diffusion of a new product in an online setting is actually formed by two parallel processes. The first one is the diffusion of viral information about the new product. The second is the diffusion process of the new product itself. Further research should be conducted to get insight into this duo diffusion.

REFERENCES

Abbasi, A., & Chen, H. (2008). Cybergate: A Design Framework and System For Text Analysis of Computer-Mediated Communication. *MIS Quarterly, 32*(4), 811-837.

Altinkemer, K., & Wenqi, S. (2008). A Multigeneration Diffusion Model for IT-Intensive Game Consoles. *Journal of the Association for Information Systems, 9*(8), 442-461.

Andrade, E. B. (2005). Behavioral Consequences of Affect: Combining Evaluative and Regulatory Mechanisms. *Journal of Consumer Research, 32*(3), 355-362.

Bass, F. M. (1969). A New Product Growth for Model Consumer Durables. *Management Science, 15*(5), 215-227.

Berger, J., & Milkman, K. L. (2012). What Makes Online Content Viral?? *Journal of Marketing Research (JMR), 49*(2), 192-205.

Bickart, B., & Schindler, R. M. (2001). Internet forums as influential sources of consumer information. *Journal of Interactive Marketing, 15*(3), 31-40.

Bollen, J., Mao, H., & Pepe, A. (2011). Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena. *Proceedings of the Fifth International AAAI*.

Breitung, J. (2000). The local power of some unit root tests for panel data. *Advances Ecoometrics, Vol 15, 2000, 15*, 161-177.

Cao, Q., Duan, W., & Gan, Q. (2011). Exploring determinants of voting for the “helpfulness” of online user reviews: A text mining approach. *Decision Support Systems, 50*(2), 511-521.

Chau, M., & Xu, J. (2012). Business Intelligence In Blogs: Understanding Consumer Interactions And Communities. *MIS Quarterly, 36*(4), 1189-1216.

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online Book Reviews. *Journal of Marketing Research (JMR), 43*(3), 345-354.

Coleman, J. S., Katz, E., & Menzel, H. (1966). *Medical innovation: A diffusion study*: Bobbs-Merrill Indianapolis.

Danaher, P. J., Hardie, B. G., & Putsis Jr, W. P. (2001). Marketing-mix variables and the diffusion of successive generations of a technological innovation. *Journal of Marketing Research, 38*(4), 501-514.

Dekimpe, M. G., & Hanssens, D. M. (1999). Sustained spending and persistent response: A new look at long-term marketing profitability. *Journal of Marketing Research*, 397-412.

Dellarocas, C., Gao, G., & Narayan, R. (2010). Are Consumers More Likely to Contribute Online Reviews for Hit or Niche Products? *Journal of Management Information Systems, 27*(2), 127-157.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing, 21*(4), 23-45.

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational Cascades and Software Adoption on The Internet: An Empirical Investigation. *MIS Quarterly, 33*(1), 23-48.

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM, 56*(4), 82-89.

Forman, C., Ghose, A., & Wiesenfeld, B. (2008). Examining the Relationship Between Reviews and Sales: The Role of Reviewer Identity Disclosure in Electronic Markets. *Information Systems Research*, *19*(3), 291-313.

Garber, T., Goldenberg, J., Libai, B., & Muller, E. (2004). From Density to Destiny: Using Spatial Dimension of Sales Data for Early Prediction of New Product Success. *Marketing Science, 23*(3), 419-428.

Garg, R., Smith, M. D., & Telang, R. (2011). Measuring Information Diffusion in an Online Community. *Journal of Management Information Systems, 28*(2), 11-38.

Godes, D., & Mayzlin, D. (2004). Using Online Conversations to Study Word-of-Mouth Communication. *Marketing Science, 23*(4), 545-560.

Goh, K.-Y., Heng, C.-S., & Lin, Z. (2013). Social Media Brand Community and Consumer Behavior: Quantifying the Relative Impact of User- and Marketer-Generated Content. *Information Systems Research, 24*(1), 88-107.

Goldenberg, J., Oestreicher-Singer, G., & Reichman, S. (2012). The Quest for Content: How User-Generated Links Can Facilitate Online Exploration. *Journal of Marketing Research (JMR)*, *49*(4), 452-468.

Gorn, G., Tuan Pham, M., & Yatming Sin, L. (2001). When Arousal Influences Ad Evaluation and Valence Does Not (and Vice Versa). *Journal of Consumer Psychology, 11*(1), 43-55.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 424-438.

Greifeneder, R., Bless, H., & Pham, M. T. (2011). When Do People Rely on Affective and Cognitive Feelings in Judgment? A Review. *Personality and Social Psychology Review, 15*(2), 107-141.

Gu, B., Park, J., & Konana, P. (2012). The Impact of External Word-of-Mouth Sources on Retailer Sales of High-Involvement Products. *Information Systems Research, 23*(1), 182-196.

Hill, R. C., Griffiths, W. E., & Lim, G. C. (2011). *Principles of econometrics* (4th ed.). Hoboken, NJ: Wiley.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control, 12*(2), 231-254.

Johansen, S., Mosconi, R., & Nielsen, B. (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. *The Econometrics Journal, 3*(2), 216-249.

Jones, Q., Ravid, G., & Rafaeli, S. (2004). Information Overload and the Message Dynamics of Online Interaction Spaces: A Theoretical Model and Empirical Exploration. *Information Systems Research, 15*(2), 194-210.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons, 53*(1), 59-68.

Kim, N., Chang, D. R., & Shocker, A. D. (2000). Modeling intercategory and generational dynamics for a growing information technology industry. *Management Science, 46*(4), 496-512.

Korfiatis, N., García-Bariocanal, E., & Sánchez-Alonso, S. (2012). Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications, 11*(3), 205-217.

Kozinets, R. V., de Valck, K., Wojnicki, A. C., & Wilner, S. J. S. (2010). Networked Narratives: Understanding Word-of-Mouth Marketing in Online Communities. *Journal of Marketing, 74*(2), 71-89.

Lau-Gesk, L., & Meyers-Levy, J. (2009). Emotional Persuasion: When the Valence versus the Resource Demands of Emotions Influence Consumers' Attitudes. *Journal of Consumer Research, 36*(4), 585-599.

Lench, H. C., Flores, S. A., & Bench, S. W. (2011). Discrete emotions predict changes in cognition, judgment, experience, behavior, and physiology: A meta-analysis of experimental emotion elicitations. *Psychological Bulletin, 137*(5), 834-855.

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics, 108*(1), 1-24.

Liu, Y. (2006). Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue. *Journal of Marketing, 70*(3), 74-89.

Ludwig, S., de Ruyter, K., Friedman, M., Brüggen, E. C., Wetzels, M., & Pfann, G. (2013). More Than Words: The Influence of Affective Content and Linguistic Style Matches in Online Reviews on Conversion Rates. *Journal of Marketing, 77*(1), 87-103.

Mahajan, V., Muller, E., & Bass, F. M. (1990). New Product Diffusion Models in Marketing: A Review and Directions for Research. *Journal of Marketing, 54*(1), 1-26.

Mahajan, V., Muller, E., & Wind, Y. (2000). *New-product diffusion models* (Vol. 11): Springer Science & Business Media.

Mahajan, V., & Peterson, R. A. (1985). *Models for innovation diffusion Sage university papers series. Quantitative applications in the social sciences no. 07-048* (pp. 1 online resource (87 p.)).

Mahajan, V., & Wind, Y. (1986). *Innovation diffusion models of new product acceptance*. Cambridge, Mass.: Ballinger.

Moe, W. W., & Trusov, M. (2011). The Value of Social Dynamics in Online Product Ratings Forums. *Journal of Marketing Research (JMR), 48*(3), 444-456.

Mudambi, S. M., & Schuff, D. (2010). What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.Com. *MIS Quarterly, 34*(1), 185-200.

Norton, J. A., & Bass, F. M. (1987). A diffusion theory model of adoption and substitution for successive generations of high-technology products. *Management Science, 33*(9), 1069-1086.

Pan, Y., & Zhang, J. Q. (2011). Born Unequal: A Study of the Helpfulness of User-Generated Product Reviews. *Journal of Retailing, 87*(4), 598-612.

Pavlou, P. A., & Dimoka, A. (2006). The Nature and Role of Feedback Text Comments in Online Marketplaces: Implications for Trust Building, Price Premiums, and Seller Differentiation. *Information Systems Research, 17*(4), 440-441.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics letters, 58*(1), 17-29.

Rishika, R., Kumar, A., Janakiraman, R., & Bezawada, R. (2012). The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation. *Information Systems Research*.

Rogers, E. (1983). Diffusion of innovations. *New York*.

Rogers, E. (2003). Diffusion of innovations: New York: Free Press.

Schweidel, D. A., Moe, W. W., & Boudreaux, C. (2011). Social media intelligence: measuring brand sentiment from online conversations. *Available at SSRN 1874892*.

Sridhar, S., & Srinivasan, R. (2012). Social Influence Effects in Online Product Ratings. *Journal of Marketing, 76*(5), 70-88.

Stacey, E., Pauwels, H., & Lackman, A. (2013). Beyond Likes and Tweets: Marketing, Social Media Content, and Store Performance. *The Center for Measurable Markting*.

Susarla, A., Oh, J.-H., & Tan, Y. (2012). Social Networks and the Diffusion of User-Generated Content: Evidence from YouTube. *Information Systems Research, 23*(1), 23-41.

Tirunillai, S., & Tellis, G. J. (2012). Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance. *Marketing Science, 31*(2), 198-215.

Watts, D. J., & Dodds, P. S. (2007). Influentials, Networks, and Public Opinion Formation. *Journal of Consumer Research, 34*(4), 441-458.

Wood, S. L., & Moreau, C. P. (2006). From Fear to Loathing? How Emotion Influences the Evaluation and Early Use of Innovations. *Journal of Marketing, 70*(3), 44-57.

Yuqing Ren, Kraut, R., & Kiesler, S. (2007). Applying Common Identity and Bond Theory to Design of Online Communities. *Organization Studies, 28*(3), 377-408.

Zeng, X., & Wei, L. (2012). Social Ties and User Content Generation: Evidence from Flickr. *Information Systems Research*.

Zhu, F., & Zhang, X. (2010). Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. *Journal of Marketing, 74*(2), 133-148.

APPENDIX

Table 21: Detailed summary of systematic sampling for subjects

Search Term	No. Username	No. Result Pages	Random Start Page	No. Page Collected
0*	8486	849	9	85
1*	20539	2054	3	206
2*	10766	1077	7	108
3*	7711	772	7	78
4*	9498	950	2	95
5*	4678	468	8	47
6*	4703	471	6	48
7*	4826	483	3	49
8*	4251	426	3	43
9*	6225	623	7	63
a*	431756	43176	5	4318
b*	424342	42435	8	4244
c*	416706	41671	5	4168
d*	469726	46973	9	4698
e*	185991	18600	3	1860
f*	203009	20301	3	2031
g*	297013	29702	8	2971
h*	214931	21494	7	2150
i*	140437	14044	4	1405
j*	421687	42169	7	4217
k*	291326	29133	2	2914
l*	273608	27361	1	2737
m*	549203	54921	4	5493
n*	207221	20723	4	2073
o*	100263	10027	8	1003
p*	277018	27702	5	2771
q*	22334	2234	8	224
r*	348799	34880	8	3488
s*	646508	64651	3	6466
t*	392047	39205	6	3921
u*	49898	4990	4	499
v*	108744	10875	3	1088
w*	161949	16195	6	1620
x*	76788	7679	5	768
y*	54323	5433	8	544
z*	83749	8375	5	838
Total	**6931059**	**693122**		**69331**

K = step of 10

Table 22: Profile of video games in terms of genre and platform

Platform / Genre	Action	Adventure	Fighting	Platformer	Racing	RPG	Shooter	Simulation	Sport	Strategy	Grand Total
Android										1	1
iPad	1	1				1					3
iPhone	14			5	2	6		3	2	5	37
Mac	1						2			1	4
3DS	4	4		1					1		10
NDS						2				1	3
PC	9	15		5	2	9	11	4	2	11	68
PS3	23	8	5	1	1	3	4	1	6	2	54
Vita	7	1	2	2	2	2	2			1	19
Wii						2					2
Xbox 360	24	2	5	6	4	5	11		6	2	65
Grand Total	**83**	**31**	**12**	**20**	**11**	**30**	**30**	**8**	**17**	**24**	**266**

Table 23: Summary of Previous Studies the effect of UGC on Business Performance

Study	**Research Subject**	**Research Site**	**Method/Model**	**LSA**	**Independent Variable**	**Dependent Variable**	**Findings**
Current study	Online game (experience & involvement product)	Online Communities IGN.com	Multiple stage	Sentiment and Richness of Information	Volume of post, UGC Sentiment, Consumer rating,	Diffusion rate Diffusion breadth Diffusion depth	Dynamic relationship between UGC and Diffusion
Tirunillai and Tellis (2012)	Multiple products	Amazon.com, Yahoo! Shopping, Epinion	Single-stage	Valence	Consumer rating, volume of chatter	Stock performance (Abnormal returns)	Chatter volume (sig. & strongest) Negative UGC (sig.) Positive UGC (ns)
Ludwig et al. (2013)	Book	Amazon.com	Single-stage	Valance Linguistic style	Consumer rating, volume of review	Conversion rate	Positive affective content (sig. & asym.) Negative affective (sig.) Congruent style (sig.)
Zhu and Zhang (2010)	Video game	GameSpot.com	Single-stage	No	Editor rating, consumer rating, volume of review	Monthly sales	Reviews more influential for less popular games and games players more Internet experience
Chevalier and Mayzlin (2006)	Book	Amazon.com Barnesandnoble.com	Single-stage	No	Consumer rating, volume of review, review length	Sales rank	Improve review increase sales, negative review more impact sales than positive

Study	Research Subject	Research Site	Method/Model	LSA	Independent Variable	Dependent Variable	Findings
Moe and Trusov (2011)	Personal care	Retailer's website	Single-stage	No	Consumer rating, volume of review	Weekly sales	Rating review (sig.), but short lived under indirect effect
Dellarocas et al. (2010)	Movie	Yahoo!Movies	Single-stage	No	Volume of review, rating, Average of rating	Weekly revenue	More reviews for less popular & successful products. Review products many others commented
Goh et al. (2013)	Apparel product	Business Fan Page on Facebook	Single-stage	Valance Richness	Direct review, indirect review, number of page view	Weekly expenditure	UGC exhibits a stronger impact than MGC on consumer purchase behavior
Duan et al. (2009)	Software	CNET Download	Single-stage	No	Total download, last week download, weekly rank, user rating	Weekly downloading market share	Online users' choice of software is heavily driven by change in download ranking and popularity information
Susarla et al. (2012)	Video content	YouTube	Single-stage	No	Age of video (days), video rating, external link, age of channel	Watching times per day	Channel centrality has impact in later stage, and channel prestige has impact in early stage

Table 24: Summary of Tests for Granger Causality using Direct Granger Procedure

Null Hypothesis: Lag	1	2	3	4	5	6	7	8	9	10	11	12
UGC Sentiment does not	49.53	79.42	5.34	57.08	12.63	10.77	5.24	4.12	3.98	5.74	1.64	2.50
Granger Cause Adoption Rate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.00
Adoption Rate does not Granger	8.91	22.59	3.08	0.22	0.06	0.09	0.16	0.51	0.81	1.28	0.82	0.85
Cause UGC Sentiment	0.00	0.00	0.03	0.92	1.00	1.00	0.99	0.85	0.61	0.23	0.62	0.60
Volume of Post does not	50.64	81.17	4.95	58.22	13.15	11.15	5.64	4.33	4.24	5.57	1.87	2.66
Granger Cause Adoption Rate	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.00
Adoption Rate does not Granger	10.57	25.53	4.36	0.57	0.09	0.16	0.28	0.63	0.63	1.09	0.87	0.73
Cause Volume of Post	0.00	0.00	0.00	0.68	0.99	0.99	0.96	0.75	0.77	0.37	0.57	0.72
Depth of Post does not Granger	11.11	2.27	1.32	0.99	0.49	0.41	0.47	0.62	0.73	0.69	0.68	0.60
Cause Adoption Rate	0.00	0.10	0.27	0.41	0.78	0.87	0.85	0.76	0.68	0.73	0.76	0.84
Adoption Rate does not Granger	16.61	6.58	2.48	1.05	0.79	1.14	1.54	1.73	1.26	1.53	1.51	1.55
Cause Depth of Post	0.00	0.00	0.06	0.38	0.55	0.34	0.15	0.09	0.25	0.12	0.12	0.10
D(Rating) does not Granger	0.01	0.18	0.54	0.23	0.41	0.34	0.29	0.53	0.80	0.78	0.62	0.55
Cause Adoption Rate	0.91	0.83	0.65	0.92	0.84	0.91	0.96	0.84	0.62	0.65	0.82	0.88
Adoption Rate does not Granger	0.12	0.12	0.98	2.25	1.20	0.75	1.86	5.44	5.05	6.82	5.81	0.57
Cause D(Rating)	0.73	0.89	0.40	0.06	0.31	0.61	0.07	0.00	0.00	0.00	0.00	0.87
Volume of Post does not	527.16	24.67	7.11	7.61	6.78	5.86	2.80	9.50	20.34	12.26	11.60	8.60
Granger Cause UGC Sentiment	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
UGC Sentiment does not	569.77	43.08	5.61	5.08	4.00	4.11	1.97	5.24	19.74	13.21	11.88	10.21
Granger Cause Volume of Post	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00
Depth of Post does not Granger	5.78	49.39	19.65	8.10	5.58	4.82	3.26	6.87	10.81	8.97	8.86	6.15
Cause UGC Sentiment	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
UGC Sentiment does not	68.99	31.59	25.26	20.50	13.14	9.28	8.03	6.00	5.40	5.11	6.25	15.20
Granger Cause Depth of Post	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D(Rating) does not Granger	4.71	1.26	0.68	1.34	0.76	0.65	0.72	0.93	1.06	0.82	1.04	0.72
Cause UGC Sentiment	0.03	0.28	0.57	0.25	0.58	0.69	0.66	0.49	0.39	0.61	0.41	0.74
UGC Sentiment does not	0.13	0.05	0.65	0.21	0.92	0.82	1.39	4.76	3.72	1.64	1.85	1.77
Granger Cause D(Rating)	0.72	0.95	0.58	0.93	0.47	0.55	0.20	0.00	0.00	0.09	0.04	0.05
Depth of Post does not Granger	4.94	58.78	25.11	9.62	6.67	5.62	3.98	7.11	10.10	8.61	7.07	5.14
Cause Volume of Post	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Volume of Post does not	69.95	31.77	26.87	21.13	14.80	10.82	9.42	7.37	6.56	6.31	7.00	15.97
Granger Cause Depth of Post	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
D(Rating) does not Granger	6.35	1.34	0.67	1.21	0.74	0.61	0.63	0.56	0.76	0.57	0.81	0.57
Cause Volume of Post	0.01	0.26	0.57	0.30	0.60	0.72	0.73	0.81	0.66	0.84	0.63	0.87
Volume of Post does not	0.09	0.02	0.76	0.36	1.41	1.00	1.51	5.38	4.17	2.24	2.60	2.07
Granger Cause D(Rating)	0.77	0.98	0.52	0.84	0.22	0.42	0.16	0.00	0.00	0.01	0.00	0.02
D(Rating) does not Granger	0.19	1.87	2.96	2.52	4.64	5.37	4.44	4.86	5.47	4.89	4.36	4.28
Cause Depth of Post	0.66	0.15	0.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Depth of Post does not Granger	0.39	0.65	0.44	0.17	0.30	0.59	0.92	0.89	0.74	0.76	0.99	1.12
Cause D(Rating)	0.53	0.52	0.73	0.96	0.91	0.74	0.49	0.53	0.67	0.67	0.45	0.34

VITA

Tung Cu received his MBA’s degree at the Asian Institute of Technology in 1999. Thereafter, he joined the Ph.D. program at Old Dominion University. After competing his first Ph.D. degree, he decided to enter the Graduate School in the Department of Information Systems and Decision Sciences at Louisiana State University. He will receive his Ph.D. degree in August 2015 and plans to become faculty at a business school.