The Emergence of Electronic Word-of-Mouth as a Marketing Channel for the Digital Marketplace

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Abstract

This study investigates the contribution of electronic word-of-mouth (eWOM) to the sales of music albums. We conducted an empirical investigation of twenty-two music albums for a period of eleven consecutive weeks. eWOM was identified as an uncertainty-reducing element in consumer decision-making. Generally, the research hypotheses were partially supported using a multivariate linear regression model. We also found a stronger correlation between some eWOM channels and sales compared to other channels. eWOM has traditionally been considered an unstructured and ad-hoc source of sentiment. Our results suggest that eWOM generated in social networking when analysed appropriately is a fairly reliable predictor of market success. It is effective as a tacit suggestion, recommendation, or referral element with viral network effects. The intended contribution of this work is in identifying eWOM as a significant information contributor in the digital marketplace.

Keywords - digital economy, word of mouth marketing, social media, e-business uncertainty, music albums, music distribution, latency window

Introduction

The emerging digital marketplace, with the Internet as a key facilitator, is an amorphous web of connections among producers and consumers (Berman, Abraham, Battino, Shipnuck, & Neus, 2007). The Internet has also presented a

synergistic opportunity for commentary, recommendation, suggestion, and referral through Word-of-Mouth WOM (Dellarocas, 2003). This seems particularly so for music and movies which elicit a following. Word-of-mouth is an alternative which rapidly creates awareness among users about a new album, products, services, and content (V. Dhar & Chang, 2007).

Burson-Marsteller and Roper Starch coined the term 'e-fluentials' in 1999 (Burson-Marsteller, 2005). This finding asserted that in traditional, offline, word-of-mouth communication one person affects the attitude and behavior of approximately another two people, whereas in eWOM one person affects the behavior of eight other people. In 2001, it was found that the e-fluentials represented about 11 million Americans, each potentially influencing up to 14 people (Burson-Marsteller, 2005). Since 1999, the number of online adults in the US has grown from about 9 percent to more than 80 percent – by more than 178 million people (Leggatt, 2007). Considering these numbers, higher computer literacy, and availability of more useful content, the e-fluentials may be expected to influence a much larger section of the society today.

Formally stated, an eWOM unit is a relevant remark made by a potential, actual, or former customer about a product or service (Hennig-Thurau, Qwinner, Walsh, & Gremler, 2004). This remark is readily available to potential customers and partners through the Internet. eWOM involves text-based, recorded, traceable, organized, and reusable one-to- many consumer interactions among strangers in cyberspace. Several studies have examined consumer-created content from the perspective of information credibility. The owner-created information focuses more on the technical details. It does not describe a product's actual performance or user perspective. Dellarocas (2003) argued that the Internet's bidirectional communication structure and the ability to artificially create large-scale word-of-mouth networks at low cost can have implications on brand reputation, consumer retention, and quality assurance. In an early study, it was found that buyers pay a 20% premium on the basis of familiarity with the seller (Brynjolfsson & Smith, 2000). The credibility of the promotional messages in online chat rooms and the implication of those new information channels on sales has been studied (Mayzlin, 2006). Specific factors like identification, promotion, loyalty, satisfaction, and participation have been studied in free-software virtual communities (Casaló, Flavián, & Guinalíu, 2010). Hence, eWOM has also been described as empowering consumers, and adding value to sales (Fiona, 2005). It is an integral aspect of the digital market worthy of continued research attention.

This study investigates the impact of electronic word-of-mouth (eWOM) on sales and revenues for digital products such as music albums. To better understand the word-of-mouth phenomenon, we refer to the terminology framework designed by the word-of-mouth Marketing Association, womMA (WOMMA, 2005). We adopt this womMA framework from an Object-Oriented perspective so that distinct eWOM functionalities, their attributes, relationships, behavior such as hits, download, streaming, sales and revenues may be derived. Table 1 illustrates the eWOM ecosystem at a high level. This framework has four main classes. The objects for these classes are:

- Participants are consumers - Senders or Receivers.
- Actions are the activities that a participant performs on WOM units, such as reading a blog post, replying or composing a comment, or recommending or suggesting content to others.
- A WOM unit is a consumer generated message found in channels such as posts, comments, and downloads.
- Venues are locations where WOM activities take place, such as social media or virtual communities.

Table 1: An Object-Oriented Framework for eWoM.

eWOM Instance	WHO	HOW	WHAT	WHERE	RESULT
eWOM Classes	Participants	Action	eWOM Units	Venues	Outcomes
eWOM Classes Properties	Demographics	Source Diversity	Polarity	Audience	Referral Value
	Credibility	Distribution Spread	Sentiment	Population	Positive, Neutral, or Negative

Adapted from the WOM Marketing Association (WOMMA 2005)

Each class has its own set of attributes. For example, participants have demographics. Outcomes are the impacts of the WOM episode, such as consuming a product or inquiring about it. It was useful to cast the eWOM ecosystem in an OO framework so that it may be subsequently instantiated with data across various classes, objects, and associations. With reference to the womMA framework (WOMMA, 2005), we identified roles pertinent to our study of music as shown in Table 2.

The remainder of this paper is organized as follows. The next section reviews the scholarly literature on WOM communication in the context of the Internet and online communities. Following this in the third section is a conceptual model from which we derive our research hypotheses. In the section describing our research method are data collection and analytic procedures. We then have separate sections reporting the results of our field investigation and a discussion of our key findings. We end the paper with some concluding remarks about limitations and further work.

Background Review

WOM interactions have been a topic of considerable importance to communication researchers and practitioners. Early studies on WOM have shown that it has a considerable impact on consumer decisions (Arndt, 1967; Bone, 1955; Engel, Blackwell, & Kegerreis, 1969; Katz & Lazarsfeld, 1955; Richins, 1983), and helps to provide a good post-purchase perception. The antecedents and consequences of online WOM have also been identified using the Opinion Leadership process (Bone, 1955; Sun, Youn, Wu, & Kuntaraporn, 2006).

In the past decade, online shopping has crossed the chasm to become particularly prevalent, especially among the young and affluent (Leggatt, 2007). However, due to the quality concerns and other consumer perceived risks (Chai & Kim, 2010), the challenges of e-shopping, particularly with respect to familiarity and mistrust, have begun to surface (Salaün & Flores, 2001). Online customers, therefore, need useful, reliable, and trustworthy assessment about a product before making a purchase. Online systems and electronic-Word-of-Mouth (eWOM) help consumers make such informed decisions.

Table 2: eWOM Classes and Objects for Music Album Study.

eWOM Classes	Sample Class Objects
Participants	Video Sharing site users
	Social Networking site users
	Bloggers and blog visitors, commenter, viewers, video uploaders.
Actions	
Creations	Creating a blog, or uploading the video.
Distributions	Making a blog or comment public.
Receipts	View a video or listen to a song; Read a comment for an album or a blog post.
WOM Units	
	A blog/blog post about the album
	A video from the album
	A comment on the album video/audio
Venues	
	Blogs
	YouTube
	MySpace
Outcome	
	Consumption- purchasing the album

By eWOM we mean Internet based peer-to-peer communication of a message or information. It differs from the face-to-face communication and traditional WOM, in several ways. First, the Internet allows people to reach many other people in a one-to-many manner with cascading effects similar to that of the mass media (Hennig-Thurau et al., 2004). Also, email messages are similar to inter-personal communication in that they can be personalized for the recipient (Phelps, Lewis, Mobilio, Perry, & Raman, 2004). Second, online communication is written, so it is more formal and insightful than the traditional WOM as characterized by Marshall McLuhan's "the media is the message" doctrine which considered communication technology as an embodiment of information being conveyed (Griffin, 2003). Thirdly, the information in eWOM is accessible to the user anytime, even when the creator of the information is absent (Godes & Mayzlin, 2004; Reichheld, 2003).

eWOM affects the reputations of products, brand, and complementary goods (Amblee, 2008). Online customer behavior and purchase decision is governed by trust more than by the product price (Reichheld & Schefter, 2000), corroborating the finding of Brynjolfsson and Smith (2000) and Brynjolfsson, Hu, and Smith (2003). Consumers freely comment online on various products such as apparel, books, electronic goods, games, videos, music, beverages, and wine in order to share either good or bad experiences (Sun, et al., 2006; Welker, 2002; Wilson & Sherrell, 1993). Various studies have been done on the effect of eWOM on books, movies (Fiona, 2005), bever-

ages, electronic products, and other items from a sales perspective (Dellarocas, Zhang, & Awad, 2007; Godes & Mayzlin, 2004; Hennig-Thurau, et al., 2004). Online video consumption is a leading activity of a teenager's typical day (Nielsen, 2009). Recent studies have also been done on using micro blogging as an online WOM tool by marketers (Jansen, Zhang, Sobel, & Chowdury, 2009). Hence, there is considerable agreement that eWOM is a factor in developing or managing brand and reputation (Amblee, 2008; Burson-Marsteller, 2005; Fiona, 2005; Welker, 2002).

Valck, Bruggen, and Wierenga (2009) examined the effects of virtual communities on consumer decision making. They focused on the heterogeneous composition of community members compared to the traditional reference groups, using iterative content analysis, in order to examine the impact of eWOM as characterized by the aptly colloquial 'word-of-mouse' (Sun, et al., 2006; Valck et al., 2009). Trust building theories that categorized the online factors into 'calculative' and 'capability' processes before using a hedonistic pricing model have been studied. Besides, higher positive feedback increased the ending price, while higher negative feedback count significantly reduced the ending price of the auctioned item (Zhou, Dresner, & Windle, 2009).

Lee and Lee (2009) have studied how consumers draw inferences about quality from online product information. In their study, they were able to model the consumer decision process for different products in view of the changing WOM sentiments, succeeding in establishing a relationship between the pervasiveness and persuasiveness of eWOM. Richins (1983) had also earlier hinted at the possibility of negative consequences of adverse WOM. While variables and fixed effects comprise the bulk of observed variation, it has been claimed that the consumer expectation variance attributable to word of mouth is approximately 10 percent (Moul, 2007). There are other more conclusive findings to show that consumer-created information is more credible than seller-created information (Wilson & Sherrell, 1993). A customer's tendency to recommend a product to others is a better performance predictor, it has been claimed, than the traditional measures such as customer satisfaction (Reichheld, 2003). Davis and Khazanchi (2008) suggest that it's not just the increase in the volume of reviews on an ecommerce site but the combination of product category, product views, and number of online reviews that are statistically significant for unit sales.

The net effect of the literature review is that eWOM is a phenomenon worthy of investigation in terms of bringing about tangible benefits to sales and revenues and not limited to the previously well-studied relationship to brand, loyalty, reputation, and trust. In the era of web 2.0, eWOM forms a natural antecedent to social networks, communities, and media.

eWOM occurs through different channels: e-mails, discussion forums, instant messaging, mobile short messaging services, news groups, and social networking sites. Some researchers have also associated eWOM with viral marketing (Kharif, 2000; Welker, 2002). In our study, we shall focus only on the sharing of opinions, evaluations, and experiences as eWOM. Hence viral marketing, email, mobile messaging, and other forms of eWOM are excluded from the current scope so as to limit the interactive effects.

Dellarocas (2003) has specified the conceptual foundation of online feedback mechanism for eWOM. However, his framework is limited to feedback per se rather than eWOM and uncertainty reducing channels. A model to quantify WOM effects had also been developed by Moul (2007). In addition, Hogan, Lemon, and Libai (2004) described a manner in which Customer Lifetime Value (CLV) could be derived by examining ripple effects.

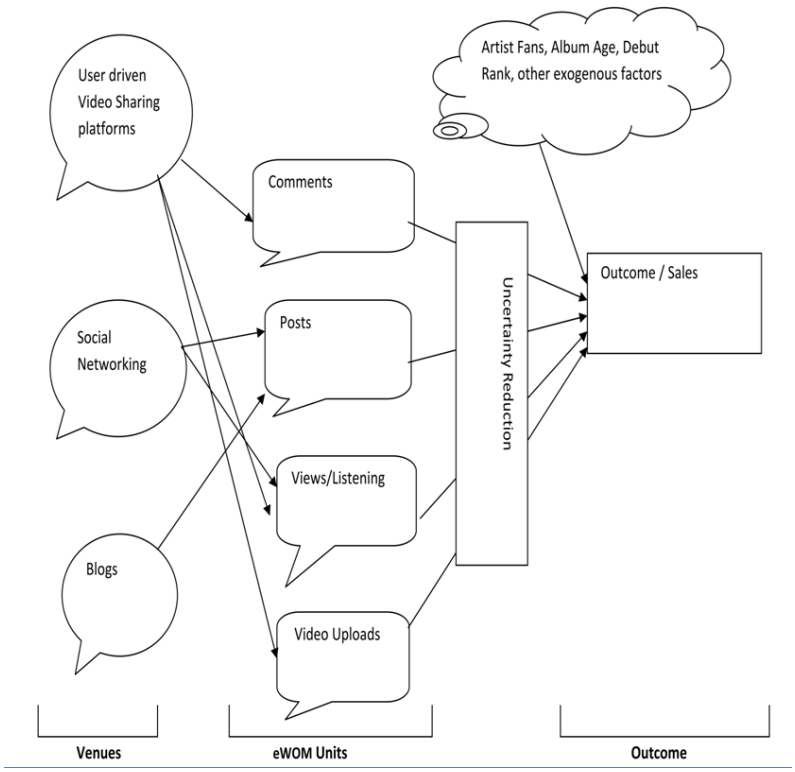

Figure 1: Instantiation of the Object-Oriented Framework for eWOM Marketing.

Following our literature survey, we developed a framework that would synthesize the association between eWOM and market impact. Figure 1 provides the key constructs (or objects) we use in our framework. It illustrates three important sources of uncertainty reduction for music consumers. The manner in which blogs and online discourses may be used by businesses for effective marketing and empowering the consumers has been frequently highlighted (c.f. Amblee, 2008; Dellarocas, 2003; Dellarocas, et al., 2007; Hennig-Thurau, et al., 2004; Hogan et al., 2004; Lee & Lee, 2009; Moul, 2007; Phelps, et al., 2004; Singh, Veron-Jackson, & Cullinane, 2008; Sun, et al., 2006; Zhou, et al., 2009). We may, therefore, consider blogs and social networking posts as important sources of eWOM. A recent study found that people not only seek opinions on social media sites but they also act on those opinions (Jansen, Sobel, & Cook, 2010). In our framework, the venue class is on top of the hierarchy. It has been used to instantiate three venue objects: blogs, user-driven video sharing platforms, and social networking sites. At the next level, the eWOM unit class produced five eWOM unit objects: Comments, Posts, Views, Listenings, and Video uploads.

- Comments are negative, positive or neutral statements posted on an album video on a forum such as YouTube. This may be measured by sentiments.
- Posts are album related statements on web 2.0 blog or social networking sites. This may be measured by volume, frequency, or popularity. Blogs represent interactive web 2.0 features which allow users to leave comments on the posts. Blogs are maintained by music fans or artists. Social networking sites, such as MySpace, were widely used in the US by people to share posts about music albums.

- Views represent the relative popularity of an album in terms of interest shown by the online community. They are measured by the total number of times an album video has been viewed.
- Similar to the views are listenings, which represent the number of times an album song has been listened to on MySpace.
- Video Uploads represent the ability of a community to participate with video commentaries. They are measured by the number of videos uploaded on YouTube for an album.

The eight above-mentioned objects may provide the necessary eWOM which helps in reducing the uncertainty of album purchase.

Methodology

From our framework, six hypotheses were derived. We hypothesize that the different channels used to spread eWOM have different impacts on sales. Hence the following are the six research hypotheses we have derived.

H1: eWOM represented by comments expressed in YouTube significantly impact album sales.

H2: eWOM represented by the number of times a video has been viewed on YouTube significantly impact album sales.

H3: eWOM represented by the number of videos uploaded on YouTube significantly impact album sales.

H4: eWOM represented by comments posted on blogs significantly impact album sales.

H5: eWOM represented by postings expressed in MySpace significantly impact album sales.

H6: eWOM represented by number of times an album has been listened to in MySpace significantly impact album sales.

Note that the above research hypotheses are permutations of the three venues and five eWOM units derived from the OO framework and collectively investigate the impact of eWOM on album sales.

We may now analyze how eWOM for music albums impacts their sales and hence affects the uncertainty a consumer has about a particular creative product – in our case, music albums (Chai & Kim, 2010). To the best of our knowledge, there are few studies on the effect of eWOM in music and the creative industries. Consequently, there is a need to understand the eWOM in the music context. Thus, the model proposed in this section attempts to prescribe a positive relationship between eWOM constructs, venues, and outcome in the form of sales. In the next section, we outline a series of steps that tests our framework empirically.

Recall that our research aims to understand consumer usage of web 2.0 tools such as MySpace, YouTube, and others as effective, revenue enhancing WOM channels for music albums. More specifically, which particular eWOM mode is the most effective predictor of sales and revenues? Hence we analyzed the impact of different eWOM modes on music sales for 22 albums over 11 weeks from the different channels defined in our eWOM framework in Figure 1.We also considered the following additional questions: Do other independent variables also impact album sales? For instance, how long does a particular eWOM episode last? This relates to the notion of a "lagged effect" which will be described later.

It would have been interesting to use data from amazon.com, the largest and most profitable Internet retailer, as the primary source for the study but such data was not forthcoming as the company declined to collaborate in this research.

Analytic Modeling and Measurement

The modeling of our framework using the objects identified and then developed into hypotheses was straight forward. The following (see Table 3) are the assigned dimension numbers (d-values) of various instances of eWOM investigated.

Table 3: eWOM Dimensions.

eWOM dimension	d-Value
YouTube Comments	1
YouTube Views	2
YouTube Video Uploaded	3
Blog Posts	4
MySpace Postings	5
MySpace Listenings	6

We refer to the eWOM units with dimensions, using Table 3 for an effective mapping. The dependent and independent variables are expressed in formula 1 and 2 in the Appendix.

There are factors that could influence our result, which varies from album to album. Consider any artist, who has a number of fans. When this artist releases a new album, the already existing fans are more likely to purchase his album. Similarly, the number of weeks an album has been on the charts gives it more visibility than an album from a debutant.

To model the uncertainty reduction, we include three control variables which are present in the environment. By definition, a control variable is one that would affect the dependent variable but is not easy to manipulate. For that reason, it is imperative to maintain it constant as the relationship between dependent and independent variables is investigated. For instance, in investigating the relationship between IT budgets and organizational effectiveness, a researcher may wish to specify firm size, industry sector, global presence, and market conditions as control variables which may be expected to influence this relationship. We admit that there could be other control variables such as the state of the economy (consumers cut entertainment spending during lean years), recognition (Top Ten charts), awards (Grammies), music concerts during world tours, and sentimental factors (e.g., the spike in sales of Michael Jackson's albums upon his death). However, we have restricted the study to the following control variables in addition to the dependent variables given in Table 4 since they could be measured more reliably:

a) Rank = 1: indicating the initial rank in week 1 of an album when it appeared on the Billboard charts (The unit of observation (UB) in this case is the initial rank value with which an album entered the billboard charts).

b) Fans: indicating the number of fans of the album's artist (UB = number of fans who participate in eWOM for each media when possible, for example in MySpace).

c) Weeks in Chart: indicating the number of weeks the album had been on billboard Top 200 rankings since such data were available (UB = number of continuous weeks an album has been on the Top 200 rankings).

d) Lag: indicating the impact of an eWOM episode not immediately but in the weeks following (UB = number of weeks after eWOM was first emitted).

Table 4: Variables and Measures.

Variables	Measures
Dependent	
Total Music Albums Sold from Week 1 to Week 11	Total number of Albums Sold for a subset of the same 20 Albums from Week 1 to Week2
Independent	
eWOM from Blog Posts from Week 1 to Week 11	Total number of Blog postings per Week from the subset of Albums under study
eWOM from YouTube Comments from Week 1 to Week 11	Total number of Comments expressed in YouTube per Week from the subset of Albums under study
eWOM from YouTube Views from Week 1 to Week 11	Total number of Videos Viewed in YouTube per Week from the subset of Albums under study
eWOM from YouTube Video Uploads from Week 1 to Week 11	Total number of YouTube Videos uploaded per Week from the subset of Albums under study
eWOM from MySpace Postings from Week 1 to Week 11	Total number of Postings in MySpace per Week from the subset of Albums under study
eWOM from MySpace Listenings from Week 1 to Week 11	Total number of albums listened to per Week from the subset of Albums under study
Total eWOM activity from Week 1 to Week 11	Total number of Weekly eWOM from the above measures of independent variables for the subset of Albums under study

Data Collection

We focused the data collection on the US market since data were readily available. We looked at other music sites, eWOM venues, and online communities before deciding on YouTube, MySpace, and relevant consumer blogs for our study. Although portals such as smashitsusa.com, community.mtvmusic.com and several others have a considerable user base, their contribution to the music albums' eWOM is minimal compared to the sources we decided to use. The exponential growth of MySpace and YouTube is further evidence of the multiplier effect of eWOM suggested by Burson-Marsteller (2005).

Godes and Mayzlin (2004) identified the two dimensions of eWOM as Volume and Dispersion. Volume is measured as the number of views at a particular time. A higher number of views implies that more people are aware of the music album. Dispersion is an indication of how well the eWOM message is spread (Godes & Mayzlin, 2004), that is, how many others have received the message. We gathered volume and dispersion data from different social networking sites; however, there is no reliable way of measuring the degree of dispersion in our study. For example, YouTube records the number of views and allows anyone to post their comments for free. The comments and the number of views are useful in determining the popularity and probable effect on album sales. However, there was no way of determining the dispersion of these comments and views.

Therefore, for the purpose of this study, we gathered weekly eWOM data from the Internet and weekly album sales ranks from Billboard Magazine (Billboard Charts, 2009), the leading trade journal for the pop music industry.

We consider music albums as hedonic (as opposed to functional) products - whose consumption is primarily characterized by an abstract enjoyable experience (R. Dhar & Wertenbroch, 2000). They are similar but not identical to experience goods which require direct usage in order to obtain assessments about product qualities. The attributes provided by this kind of product cannot be easily mimicked by other content producers. On the other hand, features offered by utilitarian products can be mimicked (Moe & Fader, 2001). Since our product of interest is a hedonic one and its attributes are abstract, consumer opinion and experience are all the more important. This information provides a prospective consumer with an indirect/virtual experience and helps reduce the uncertainty associated with the attributes.

We apply the Uncertainty Reduction Theory from Berger and Calabrese (1975) on our product of interest. Through this theory we can understand how potential consumers use online reviews / comments and other statistics to interact with other consumers (Berger & Calabrese, 1975) and hence (a) infer product hedonic attributes, (b) reduce uncertainty, and (c) push towards a final decision (Hu, Liu, & Zhang, 2008). Also to be noted is that in our study the price of goods and the reviewer quality are not so important because the price of one album is not very different from other albums, and the eWOM content is user generated and may either be refuted or remain unpopular.

We collected eWOM data using the Google search engine, which permitted us to retrieve data for a specific period of time, specific geographical area, and from a specific site or domain. To retrieve the postings from blogs, we used Google Blog Search. In evaluating which tool to use in order to search blogs, we tested Technorati (technorati.com), BlogScope (www.blogscope.net – a project from the University of Toronto), in addition to Google Blog Search. Technorati provided a reduced number of results for specific search using the same key words compared with the other two search engines. We decided against using BlogScope, since it required special permission to access the full set of results during data collection.

The Google Blog Search was hence most useful for collecting the number of blog posts for the music albums. The data collection proceeded as follows. We gathered all the available postings for each album. MySpace was used to gather the number of times the album had been played and the number of posts. From YouTube, we obtained the data for the number of uploads, views, and comments for the albums. Searches were conducted based on keywords such as album title and artist name, country of origin, and the period of observation. We collected eWOM data for a period of 11 weeks for 22 albums – as we found that the data was sufficient for analysis. Some prior research had used shorter periods of time (V. Dhar & Chang, 2007; Hu et al., 2008) and we were also guided by practicality.

In all the search results that we came across, one major factor was the relevance of the hits to our purpose. For example, searching for an artist “Pink” and an album “Funhouse” retrieved many results. However, some of these results, such as a non-ranked list of songs in the album or images without any comments, are not relevant to the related eWOM. These results were unusable because of the absence of any views, comments, and posts on the music album. Hence, we arrived at the criteria below for filtering the relevant results from the irrelevant ones:

a) The data must be from the United States since music ranks are territorial and the sales ranking data we obtained were for the US market.

b) The eWOM data was restricted to English due to content analysis carried out.

c) The data must be relevant to our research objective in the sense that there must be some manifestation of eWOM in the search results.

Using the above criteria, we were able to select twenty-two albums which also remained in the Billboard rankings during the eleven week window of analysis. These selected albums are tabulated in Table 6.

For eWOM originating from YouTube, we used sampling to deduce the total eWOM count. We sampled 20% of the total results and then extrapolated the eWOM counts to the total number of relevant results. We also collected the number of all the available postings and listening count from MySpace. Sales rankings and figures were collected from Billboard Magazine (Billboard, 2000), and Paul Grein's Yahoo blog (new.music.yahoo.com/blogs/chart_watch/).

In the manner described above, data collection was carried out over a 6 month period in the later half of 2009.

Normalization and Transformation of eWOM Data

Normalization of the collected data is essential due to the non-comparable range of values obtained. Since we have eWOM counts from different units, we normalized the eWOM count using formula 3 given in the Appendix.

The justification for such normalization was to allow for cross comparison given the diverse venues, eWOM units and impact values. By comparing the range of each eWOM unit and using a scaling factor for the measured values of the unit, we were able to calibrate the data on a standard measurement scale.

Once the normalized value was calculated using equation (2), the individual unit count and collective count were tabulated for further analysis. Hence we did not discard any of the data collected.

We were specifically interested in the impact of different dimensions of eWOM on music sales. Gaining access to the actual sales figures of a particular album for all the 11 weeks was not possible. Such data is not made publicly available by the music labels. Therefore, we adopted a statistical inference approach by using the Power-Law distribution method, for converting the weekly ranks to approximate weekly sales figures.

Power Law distributions occur in many phenomena of scientific interest. The law has also been applied for rank-to-sales estimation of books and movies (Brynjolfsson et al., 2003; Chevalier & Goolsbee, 2003; Clauset, Shalizi, & Newman, 2009; Hoogenboom, Otter den, & Offerhaus, 2006; Vany & Walls, 1996). The effectiveness of Power Law distribution has been used when working with ranks so as to provide a basis for transforming the distribution of data from cluttered to more spread out. In our study we estimated sales probabilities from the billboard magazine ranks using such a Power Law distribution and the formula for calculating the exponents for the Power Law distribution (See formulas 4 and 5 in the Appendix).

Using the Power of Law distribution, we calculated values of α for each week and then a general value from all the available data for 11 weeks. Linear Regression between the Log values was performed using SPSS (v.17) to determine goodness-of-fit. The scaling parameter, α, in our study, was found to vary from 2.37 to 3.21. With this model, the goodness-of-fit was 0.89 with $p =< 0.05$, which may be considered sufficiently robust. Since the sales values do not follow a normal distribution, the analysis was conducted on the log value of the calculated sales. We used these values as a proxy for sales. We could have used the Granger test of Causality to establish a causal relationship between eWOM and album sales, but we were more interested to determine if

there was a time window for eWOM than linking antecedents to outcomes at this point of our research.

Descriptive statistics were computed for both independent and dependent variables. Bivariate analysis was also carried out to investigate potential associations between independent and possible confounding variables. As mentioned earlier, the data was analyzed using Multi-Linear Regression to determine which eWOM variables had a strong association with sales. This was first done without considering eWOM latency, and subsequently by considering latency. The regression model was tested week-by-week with the relevant independent variables. Collinearity refers to the possibility of some degree of redundancy or overlap among independent variables. This was minimized by selecting the SPSS option that controls for such effects.

Latency incorporates the delayed effects of eWOM in the time periods (weeks) that follow. In other words, rather than consider the effects of eWOM in the same time period (week) of its occurrence, latency allows us to study the lag effects of such sentiments going around. This was the basis of our belief that latency is a factor to be considered in our model. For instance, eWOM for week1 could have an effect on week 2, and probably in week 3, and potentially in week 4. In general, latency are the effects of a lag or time delay which occurs in any dynamic system of interest.

Findings and Discussion

An examination of trends revealed that the rank curves of five of the twenty-two albums were decreasing and steep sloped. A further eight of them had a "U" shape with a declining tendency. Four had a moderately declining slope. Only two albums came into the chart with a lower rank and reached their peak ranks some weeks later. Seventy five percent of them had an initial rank between one and ten, twenty percent had an initial rank between eleven and twenty, and five percent had a rank higher than forty. Ninety percent of the albums debuted with their highest rank and started to decline on the rank charts. Conversely, only ten percent started with a lower rank and later achieved their peak ranks. In general, the albums started with the highest rank and later declined. Such was the popularity profile of the albums selected for the study.

Table 5: Multivariate Linear Regression Results (without considering latency effects).

	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11
Model Parameters (R^2, p values)	R^2=0.85 p=0.00	0.80 0.00	0.77 0.00	0.63 0.00	0.59 0.00	0.67 0.00	0.54 0.00	0.69 0.00	0.77 0.00	0.69 0.00	0.59 0.00
H_1	X	X	X	X	X	X	X	X	0.02	0.04	X
H_2	X	X	X	X	X	X	X	X	X	X	X
H_3	0.03	X	X	X	X	0.04	X	X	X	0.00	X
H_4	0.02	X	X	X	0.00	X	X	X	X	X	X
H_5	X	0.02	0.02	X	X	X	0.05	0.00	0.00	0.01	0.01
H_6	X	X	X	X	X	0.03	X	0.01	0.00	X	0.01
Weeks in Chart	0.00	0.00	0.01	0.05	X	0.00	X	X	X	X	X
Rank = 1	0.01	0.02	X	X	X	0.02	X	X	X	X	X
No. Fans	0.00	0.01	0.01	0.00	0.00	0.00	0.03	0.02	0.00	X	0.03

X=research hypothesis not supported

Table 5 shows the research hypotheses that were accepted with p =< 0.05 (i.e., 95% confidence or better) when latency was not considered. For each week (given by column header week 1 … 11), the first row gives R^2 values indicating the amount of variance explained, and p values giving the significance of the test. The next six rows give the significance (p values) of the six research hypotheses tested week-by-week. The last three rows give the p values for the three control variables (weeks on the best-seller charts, rank in week 1, number of fans). The "X"s indicate research hypotheses not accepted or the above control variables not significantly effecting sales for that particular week.

In seven out of the eleven weeks - 63.6% of the time - H5 was accepted; making the number of postings expressed on MySpace the best eWOM predictor. The second best predictors were the number of times an album was listened to on MySpace (H6), which explained album sales in four weeks (36.36% of the time). The third best predictor was the number of videos uploaded on YouTube (H3), which explained album sales in three weeks (27.27% of the time). "YouTube comments" (H1) and "comments posted in blogs" (H4) were predictors for only 2 weeks. eWOM represented by the number of videos viewed in YouTube (H2) was not accepted in any week.

Table 6: Multivariate Linear Regression Results (considering latency effects).

	Week 2	**Week 3**	**Week 4**	**Week 5**	**Week 6**	**Week 7**	**Week 8**	**Week 9**	**Week 10**	**Week 11**
Model Parameters (R^2, p values)	0.79 0.00	0.56 0.00	0.7 0.00	0.59 0.00	0.69 0.00	0.56 0.00	0.68 0.00	0.38 0.03	0.56 0.00	0.62 0.00
H_1	X	X	X	X	X	X	X	$(0.01)_9$	X	X
H_2	X	X	$(0.05)_1$	$(0.02)_4$	X	X	X	X	$(0.01)_7$ $(0.00)_8$	$(0.00)_7$ $(0.00)_8$
H_3	X	$(0.01)_2$	$(0.02)_1$	X	X	X	X	$(0.01)_7$	X	X
H_4	X	$(0.01)_2$	$(0.02)_2$	$(0.04)_3$ $(0.05)_5$	$(0.02)_3$ $(0.03)_5$	X	X	X	$(0.02)_8$	$(0.01)_{10}$
H_5	$(0.02)_1$	X	X	X	X	$(0.03)_4$	$(0.00)_4$	X	X	X
H_6	X	X	X	X	X	$(0.05)_6$	$(0.01)_8$	X	X	X
Weeks in Chart	(0.00)	X	X	X	X	X	X	X	X	X
Rank=1	(0.03)	X	X	X	X	X	X	(0.03)	X	X
No. Fans	(0.01)	X	(0.00)	X	(0.01)	(0.02)	(0.02)	X	X	X

X = research hypothesis not supported

Table 6 shows the research hypotheses that were accepted with p =< 0.05, when eWOM latency or lagged effect was considered. This was done by including the impact of eWOM on sales and ranks in subsequent time periods rather than during its first occurrence. That is, sales data from subsequent weeks were correlated with the number and type of eWOM episodes for each given week. For example, in week 2 the independent variables for week 1 were included in the model. There are double entries of p values in some cells. For example, the intersection of week 5 and comments posted on blogs (H4) has two p values, $(0.04)_3$ and $(0.05)_5$. This is attributable to the comments expressed on blogs on week 5 and comments expressed on blogs in week 3 which explain album sales in week 5. Once again, the table shows the research hypotheses that were accepted with p=< 0.05 (i.e., 5% confidence or better) but this time when latency was considered. For each week (given by column header week 2 … 11), the first row gives R^2 values indicating the amount of variance explained and p values giving the significance of the test. The next six rows give the significance (p values) of the six research hypotheses tested week-by-week. In the-

se rows, significant p values are represented within parenthesis, and weeks are represented with subscripts. The last three rows give the p values for the three control variables. Once again, the "X"s indicate research hypotheses not accepted or the above control variables not significantly effecting sales for that particular week.

In eight out of the ten weeks tracked - 80% of the time - H4 was accepted, making posts in blogs the best eWOM predictor in the period studied. H2 associated with the number of videos viewed on YouTube was accepted 60% of the time. H3, which represents the number of videos uploaded on YouTube, was accepted in 30% of the weeks. H5 was accepted in three out of ten weeks. In 20% of the time, the number of times an album was listened to on MySpace (H6) were accepted, and in 10% of the time, hypotheses associated with YouTube comments (H1). Analysis of Table 6 follows the same logic as Table 5, the only difference being that the former has ten weeks since the first week does not have eWOM history (latency).

Comparing Tables 5 and 6, we note that control variables also had a significant impact when latency was not considered. In fact, the number of fans had impact on ten out of eleven weeks. The number of weeks an album has been in the chart influenced eight of the eleven weeks. The initial rank of an album also had a significant impact in five weeks. When latency was considered, control variables had less impact. Number of fans, first rank, and number of weeks an album had been in the charts had impact on 50%, 20%, and 10% of the weeks compared to 90%, 27% and 36% respectively without latency.

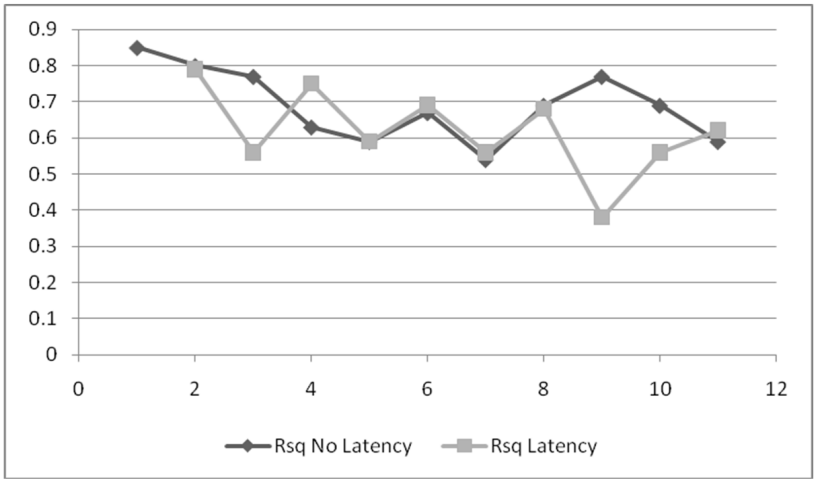

Figure 2: Week-by-Week Tracking of R^2 Values.

Our study basically undertook to demonstrate the impact of eWOM on music album sales with and without latency effects. Figure 2 is a plot of the weekly correlation values obtained from the two models shown in Tables 5 and 6. It is evident that they are comparable and do not show a clear difference between the models. More specifically, there is not a great variation of the R^2 values of the model with latency and the model without latency. The explanatory power of the models with latency is not better than models without latency. However, the model with latency offers a more complete understanding of eWOM since it involves more variables. Hence, the regression model with latency is considered superior to the one without latency since the other control variables have a greater impact on the model without latency. In other words, latency explains more of the variance when considered as an additional control variable.

The latency of an eWOM message's impact lasted for two and a half weeks on average. We call this period – the eWOM 'latency window.' This is essentially the average period for which the eWOM episode impacted sales. In other words, beyond this period the eWOM episode did not

significantly impact album sales. Thus, after this period of time, the eWOM episode may not affect our models. However, there were a few exceptions: comments in MySpace in week 4 had effects on the sales in week 8. Collinearity between variables had been present in all weeks, and its effects had been eliminated by selecting the SPSS option.

Hence we may claim that the empirical research shows that eWOM is generally useful in predicting consumer behavior in digital markets. Music albums are hedonic products - whose consumption is primarily characterized by an affective experience (R. Dhar & Wertenbroch, 2000). Since our objects of study are hedonic products, it makes sense that consumer feedback and experience are all the more important as hedonic attributes are abstract. This feedback provides a prospective consumer with an indirect experience and helps to reduce the uncertainty associated with the quality of such experience goods.

Although our results show that some user-generated content in the form of eWOM is a helpful indicator of album sales, conventional factors cannot be disregarded as shown by the control variables. Ninety four percent of the albums studied had initial ranks under eighteen. Besides, ninety percent of the albums obtained their maximum rank in the first week and later descended to lower ranks. The initial rank may be a proxy measure of the effectiveness of the promotion strategies adopted by music producers. However, the number of fans cannot be solely attributed to successful promotion tactics. Number of fans may also be influenced by personal music choice, cliques, fashion, and other exogenous factors. Weeks in the charts may be influenced by a match between an album and the popular choice, promotion, and eWOM. At this point, we may conjecture that these variables were found to be highly relevant in such an analysis.

Our results also suggest that some forms of eWOM - particularly, YouTube and blogs - may over-ride successful marketing strategies when an album matches the popular choice. By popular choice, we mean content that generates high views, downloads, and positive eWOM; possibly translating to monetisation. As was the case in our study, our sample of albums came from popular hits. However, further research is needed to identify the role of eWOM for artists who match the popular choice of some groups but do not have high marketing budgets, such as “Flo Rida” or the lesser known “Kid Cudi”. Further research is required to study the impact of eWOM when the hedonic product does not match the popular choice but has high network effects nevertheless.

Notwithstanding the above caveat, the key finding of our study is that eWOM latency affects e-markets, though this may not be statistically significant. But it is reasonable to suggest that promotional efforts may have to consider the maximum latency length for traditional promotional campaigns as well as viral distribution. The Internet, while facilitating new types of distribution, has eliminated some intermediaries especially in viral chains which occur when a content provider permits the syndication, aggregation, and distribution of content-free of Digital Rights Management (TICSC, 2008). In other words, if popular content may be circulated for free, it will.

Hedonic content undergoes tremendous transformation when it evolves from physical entities (cassette types, video cassette, CD, DVD, game cartridges) to an intangible one (MP3 file). This situation arises from four major disruptions in the traditional media industry caused by digitization and convergence: (1) the cost of reproduction and distribution is practically zero (Anderson, 2004), (2) the enforcement of rights is difficult (Seidenberg, 2009), (3) the use of traditional distribution has been drastically changed(Lam & Tan, 2001), and (4) ease with which digital products may be shared over the Internet (TICSC, 2008). This underscores the role of eWOM as a significant contributor to market outcomes. Under these previous conditions, we can more than speculate about the potential effects of eWOM. For example, currently differentiation in price may be explained when a distributor has earned the trust of the market, as in the case of Amazon.com. Otherwise, eWOM may have an effect of identifying the distributor with the lowest price. Another instance is when a desirable product may have a shorter time window after which

any negative eWOM message would freely circulate. The market for hedonic products is in constant change. Modifications to copyright law may turn out to impact the distribution of digital content in the long term, with eWOM playing a role in the marketing as well as distribution of the product.

Conclusion

Social media, such as blogs and wikis, provide consumers with influential eWOM characteristics for the expression of points of view. Tools that support eWOM (namely, the so-called web 2.0 functionalities) may emerge as a trusted source of recommendations for consumers and feedback mechanisms for marketers. The results of our study suggest that eWOM generated in such social media may be effective predictors of album sales in a given time window. We may conclude that both the latency and the no-latency models are (statistically speaking) equally useful in understanding the impact of eWOM. However, the latency model appears more significant on YouTube and personal blogs but does not appear to be important for MySpace. Personal blogs are key among eWOM, which challenges marketing knowledge. The initial rank of an album, the number of fans, and the number of weeks an album was on the top 20 charts are factors which play a significant part in generating sales and revenues. Extraneous effects such as MTV/Radio exposure, real life experiences were assumed to be negligible.

As a suggestion for further research, a Granger test of causality, which incorporates a lag between dependent and independent variables, could be performed as we work with a new data set from other regions or for other products. As well, our study of successful music albums may have created the possibility of sample selection bias, in the case of eWOM. Sentiment type - positive, negative, or neutral - was ignored and this weakens the power of prediction. These are accepted as some of the limitations of the research. Finally, since we collected all the postings from blogs and other forms of social media about the albums under study, it is difficult to generalize our findings to other products and other markets. This future research could address some of these problems by extending the data collection to a greater sample of products and markets with more sophisticated analyses of sentiments, causality, and control factors.

More specifically, from a practitioner perspective, there are several in-depth questions that may be posed. How can the amorphous context of personal bloggers be influenced to boost album sales? Does MySpace become a potent predictor with no latency because it is a more closely knit community? How can online marketing push up the number of YouTube video views? From research perspective, further questions to probe further include: Why do some eWOM channels work while others do not? Why does latency make a difference in some channels but not in others? Are there other rigorous ways (constructs, measures) of studying eWOM?

In closing, this study provides additional insights on understanding eWOM in the music context and, by extrapolation, the digital marketplace. This creates channels for the reduction of uncertainty associated with hedonic products for consumers. In addition, our results contribute to the partial understanding of the transition from a physical market to a digital one. In fact, eWOM appears to impact current sales and help retain albums in the billboard ranks of subsequent weeks – a sort of lingering memory among fans.

Tracking eWOM can also offer practical guidance to the marketplace that employs such channels as feedback mechanism since eWOM helps in positioning an album week by week. Future research could investigate the effect of eWOM in the complete life cycle of an album or single. It would also be intuitive to apply the same analysis to other digital media products such as online games, books, and movies and to other cultures and environments such as the Chinese, Indian, or Arab markets. It is intended that the research results reported here are a step in this direction of mining the content of social media for useable information predicting market success.

In closing, we concede that eWOM on some social media sites, and as measured in this study, may have some predictive power, with latency as well as without it. However, more research on digital music consumers' decision making is certainly needed, as their behavior is evolving along with the nature of the electronic market-place.

Acknowledgements

This work was supported by the Singapore National Research Foundation Interactive Digital Media R&D Program, under research Grant NRF.2007IDM-IDM00276. The authors thank the EiC and reviewers of this journal for making this a much improved version of the original submission. Many thanks are also due to Ravleen Kaur, our delightful RA and SIGIDE collaborators for their useful comments and insights.

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Appendix

Dependent variables

TAS_i: Total Albums sold during week i **(1)**

$i \varepsilon [1 \ldots 11]$

Independent variables

$ceWOM_{w}^{d}$: Cumulative value of electronic word of mouth for dimension d during week W.

That is,

$$ceWOM_{Wk}^{d} = \sum_{w=Wk-2}^{w=Wk} eWOM_{wn}^{d} \quad ceWOM_{Wk}^{d} = \sum_{w=1}^{11} eWOM_{Wn}^{d} \qquad (2)$$

where

$eWOM_{wn}^{d}$: *Normalized eWOM count for dimension d in week w.*

d ε (1,2,3,4,5,6) using the categorization shown in Table 3.

w: 1 to 11, since we are investigating the impact for 11 weeks.

Normalization of collected data.

$$[eWOM(_{w}n^{d}) = \frac{eWOM^{d}}{\max[eWOM_{\square}^{d}]} * sf^{\square} \qquad (3)$$

Where

$eWOM_{wn}^{d}$: Normalized eWOM count for dimension d in week w.

$eWOM^{d}$: eWOM count, collected for dimension d.

sf: Scaling Factor.

d: eWOM dimension coefficients, varying from 1 to 6, see Table 2.

w: 1 to 11, since we are investigating the impact for 11 weeks.

Power Law Distribution

p(x) α $x^{-\alpha}$ (4)

where

p(x): Probability of sales x.

x: sales value.

α: scaling parameter. The scaling parameter typically lies in the range 2 < α < 3.

We calculated the exponents in the Power Law using the concept of maximum likelihood estimators (MLEs).

$$\hat{\alpha} = 1 + n\left[\sum_{i=1}^{n} \ln\frac{x_i}{x_{\min}}\right]^{-1} \qquad (5)$$

Where:

n: number of data points.

$\hat{\alpha}$: Most likely estimator for the scaling parameter.

Biographies

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