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Discussion Paper

Awareness, Interest, and Purchase: The Effects of User- and Marketer-Generated Content on Purchase Decision Processes

by

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Completed Research Paper

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Abstract

Companies use Facebook fan pages to promote their products or services. Recent research shows that user- (UGC) and marketer-generated content (MGC) created on fan pages affect online sales. But it is still unclear how exactly they affect consumers during their purchase process. We analyze field data from a large German e-tailer to investigate the effects of UGC and MGC in a multi-stage model of purchase decision processes: awareness creation, interest stimulation, and final purchase decision. We find that MGC and UGC create awareness by attracting users to the fan page. Increased numbers of active users stimulate user interest, and more users visit the e-tailer's online shop. Neutral UGC increase the conversion rate of online shop visitors. Comparisons between one-, two- and three-stage modes show that neglecting one or two stages hides several important effects of MGC and UGC on consumers and ultimately leads to inaccurate predictions of key business figures.

Keywords: Social networks, consumer decision making, word of mouth, user-generated content, marketer-generated content

Introduction

With the growing number of users expressing their opinions on brands, products, and services online, user-generated content (UGC) now plays a considerable role in the marketing communication mix (Albuquerque et al. 2012; Faase et al. 2011; Forman et al. 2008). Consumers increasingly rely on UGC rather than marketer-generated content (MGC) (Escalas 2007) when searching for information about products or services (e.g., Moon et al. 2010) and for help in purchasing decisions (e.g., Chen and Xie 2008; Dellarocas et al. 2007). Social media and online social networks (OSN) have reinforced and accelerated this development (Dellarocas 2003) by offering livelier and more direct means of interaction between consumers and companies (Bonchi et al. 2011; Brock et al. 2011). On Facebook, the most popular OSN in the world, one billion active users share 684,478 pieces of content and "like" 34,722 brands or organizations – every single minute (Tepper 2012). For companies, Facebook provides special "fan pages" – corporate profiles similar to user profiles (Kim et al. 2010) – to enable them to communicate directly with their (prospective) customers. To do so, companies post MGC on the fan page's message board and users can reply or start new conversations by creating UGC. By engaging in activities on fan pages in OSN, companies hope to draw attention to their brands, products, or services (Richter and Schäfermeyer 2011; Waters et al. 2009) and, ultimately, to increase sales (Goh et al. 2013; Jahn and Kunz 2012).

But although prior research shows that MGC and UGC in OSN can indeed have a considerable impact on sales (Goh et al. 2013; Sonnier et al. 2011), it does not fully explain the processes by which MGC and UGC are translated into sales. This study contributes to closing this gap by using a multi-stage model of consumer decision-making (Hauser and Wernerfelt 1990; Shocker et al. 1991) for analyzing the effects of MGC and UGC created on fan pages in OSN on online sales. Specifically, we examine the roles of MGC and UGC in i) creating awareness for products or services, ii) stimulating interest in them, and iii) generating actual sales.

Measuring the intermediate outcomes "awareness creation" and "interest stimulation" is difficult because they are non-persistent phenomena. We suggest combining data from OSN and online shops to analyze these two stages in addition to the final purchasing decision. Separate analyses of the effects of MGC and UGC on each stage of the purchase decision process provide deeper insight into the questions of how a company's activities in OSN can i) increase awareness for the company's portfolio of products or services among customers, ii) translate increased awareness into online shop visits, and iii) convert visits into actual sales. Since prior research shows that the valence of UGC in OSN can have opposite effects on consumers' purchase intention (e.g., Goh et al. 2013; Sonnier et al. 2011), we distinguish between negative, neutral, and positive UGC.

Based on an empirical investigation of field data from a large German e-tailer, we find that the three-stage model is superior to both one- and two-stage models for explaining the effects of MGC and UGC. The results show that MGC is most effective in creating awareness among OSN users but that it is apparently not very useful for either stimulating consumer interest or convincing consumers to purchase a product. We observe the same, but weaker, effects for positive UGC. Neutral UGC, however, succeeds in creating awareness and translating it to higher conversion rates and consequently sales. Our results indicate that Facebook fan pages are an excellent instrument for low-cost awareness creation but rather ineffective in actually stimulating consumer interest and increasing sales. Interestingly, negative UGC did not affect consumers at all, contrary to findings by other studies (e.g., Yin et al. 2011).

Our contribution to research on consumer behavior in OSN is threefold: First, our results indicate that using a one-stage model of the purchase decision process is insufficient for understanding the effects of MGC and UGC on sales. Not differentiating between the single steps of the purchase decision process may mask effects and thus lead to wrong conclusions about the effectiveness of UGC and MGC. Second, our results indicate that successful creation of awareness does not necessarily lead to higher sales. Third, our results show that UGC valence plays a major role in purchase decisions and that consumers value neutral UGC most.

Related Work

OSN are "web-based services that allow individuals to i) construct a public or semi-public profile within a bounded system, ii) articulate a list of other users with whom they share a connection, and iii) view and traverse their list of connections and those made by others within the system" (Boyd and Ellison 2007, p. 211). Although OSN had originally been designed for private users (Bughin and Manyika 2007), they soon attracted large numbers of companies who have found in them the perfect platform for communicating directly with their existing customers and attracting new customers (Heidemann et al. 2012). In OSN, companies and users usually communicate through postings on corporate profile pages ("fan pages"). Companies post MGC, for instance, to promote their brands, to advertise specific products or services, or to provide general information. Users can reply to MGC or start new conversations, thus creating UGC. By actively managing their fan pages, companies attempt to strengthen the ties with their customers (Algesheimer et al. 2005; Woisetschläger et al. 2008), to draw attention to their company, brands, and products or services, and ultimately increase sales (Adjei et al. 2010).

But lively communication and frequent postings of MGC and UGC on a fan page do not necessarily translate directly into higher sales. Whether MGC and UGC have a positive or negative effect (or even any effect at all) on consumer purchase decisions depends on several factors. Prior research on UGC shows a considerable effect of the sentiment or valence expressed in the content (e.g., Chevalier and Mayzlin 2006; Chintagunta et al. 2010; Goh et al. 2013; Moe and Trusov 2011; Sonnier et al. 2011; Zhu and Zhang 2010). In research on consumer choice, purchase decisions are considered to be the result of a multi-stage decision process (Bettman 1979; Shocker et a. 1991), which typically includes the stages of awareness, interest, and final decision (De Bruyn and Lilien 2008). Consumers' information needs change during the purchasing process (e.g., Jang et al. 2012), and their appreciation of MGC and UGC varies across stages accordingly. In the first stage, consumers are usually only aware of a subset of all available products in a market (Shocker et al. 1991); products or services of companies outside the awareness set have no chance of even being considered for purchase.

The first challenge for companies is therefore raising awareness for their brands, products, or services. One way to create awareness is publishing MGC, for instance, by posting on fan pages in OSN (Fournier and Avery 2011; Gallaugher and Ransbotham 2010; Wen et al. 2009). OSN reinforce the effect of MGC because new postings automatically appear in the personal newsfeeds of all OSN users directly connected to the fan page ("fans") in addition to appearing on the fan page itself (Debatin et al. 2009). If users perceive their communication with the company to be valuable, their fan page engagement and usage intensity increases (Jahn and Kunz 2012), which also increases their awareness of the company and its products or services. Another way how awareness can be created is by (online) word-of-mouth, that is, product- or service-related UGC (Hinz et al. 2011; Iyengar et al. 2011; Van den Bulte and Wuyts 2007). Awareness for a company, its brands, products, or services increases as more UGC is created (e.g., Dhar and Chang 2009; Godes and Mayzlin 2004) and distributed (Duan et al. 2008). Higher numbers of UGC postings on fan pages increase their social interaction value, which in turn increases the fan page engagement of users (Jahn and Kunz 2012). Publishing UGC on OSN fan pages is particularly effective for awareness creation because the content also appears in the newsfeeds of all users connected to the creator (Debatin et al. 2009). This newsfeed mechanism increases the likelihood for and the speed of viral UGC distribution through network effects (Hill et al. 2006; Libai et al. 2010; Trusov et al. 2009).

After consumers have become aware of a company's brands, products, or services that appear attractive to them, they may become interested in obtaining more information (De Bruyn and Lilien 2008). Interested consumers evaluate products or services to find out whether they constitute goal-satisfying alternatives and compare them with others to determine their relative utilities (Hauser and Wernerfelt 1990; Shocker et al. 1991). Evaluating and comparing products or services is more difficult in online than offline shopping because consumers cannot test a product prior to purchase. As a consequence, pre-purchase uncertainty about its quality and the perceived risk associated with the purchase are high (Geven et al. 2008). Evaluating experience goods like books, movies, or perfume online is particularly difficult because their characteristics cannot be described objectively (Nelson 1970). Consumers usually try to reduce perceived purchase risk to an acceptable level by searching for information beyond product or service descriptions provided by manufacturers and marketers (Bettman 1973; Zhu and Zhang 2010).

After successfully creating awareness, the next challenge for companies is therefore to stimulate consumer interest by providing additional information (or access to information) that helps consumers evaluate the products or services. MGC can offer interested consumers additional cues which help them judge whether a product or service is likely to satisfy their consumption goal (Goh et al. 2013; Lin and Goh 2011). MGC that are not directly related to a specific product or service may also contribute to reducing perceived purchase risk by addressing, for instance, return and refund policies or terms of delivery. However, consumer trust in MGC is generally low (Escalas 2007): companies always have an incentive to create positive MGC, even for products or services of low quality, if their major short-term goal is to increase sales. UGC is therefore generally perceived as much more credible and trustworthy than MGC (Chen and Xie 2008; Moon et al. 2010; Senecal and Nantel 2004). In the context of OSN, Goh et al. (2013) show that information richness of UGC has a larger impact on consumer purchase behavior than of MGC. Reading other consumers' opinions of and experiences with products or services helps consumers determine the degree to which the evaluated product matches their preferences and expectations. Positive UGC increases perceived quality (Liu 2006) and reduces the perceived risk associated with a purchase (Dimoka et al. 2012). Negative UGC produces the reverse effects (e.g., Dellarocas et al. 2007; Yin et al. 2011) and may affect consumer attitudes and behavior to a greater extent than positive UGC (Yin et al. 2011).

Whether consumers ultimately decide to purchase a product or service depends on the level of perceived attractiveness (Hauser and Wernerfelt 1990) and on the perceived risk associated with the purchase (Cunningham et al. 2005). MGC can increase consumers' propensity to purchase due to its informational value (Goh et al. 2013; Lin and Goh 2011) and its persuasiveness (Meyers-Levy and Malaviya 1999; Russo and Chaxel 2010; Wu et al. 2009). Generally, however, consumers are more likely to rely on UGC (Dellarocas et al. 2007; Smith et al. 2005). Both volume (e.g., Dhar and Chang 2009) and valence (e.g., Chintaguta et al. 2010; Sonnier et al. 2011) of UGC affect consumers' purchasing decisions. Positive UGC in particular has been reported to increase sales (e.g., Zhu and Zhang 2010). Sonnier et al. (2011) confirm this finding in the context of OSN. Moreover, Goh et al. (2013) find that UGC valence has a larger effect on sales than MGC valence. Negative UGC produces reverse effects (e.g., Dellarocas et al. 2007; Yin et al. 2011) and can influence purchasing decisions to a greater extent than positive UGC (Yin et al. 2011). By contrast, Sonnier et al. (2011) report a larger effect of positive UGC than of negative UGC in OSN.

Research Model

Figure 1 summarizes our research model, hypotheses, and operationalization of the dependent variables. The following subsections describe the research model in detail.

Figure 1. Research Model
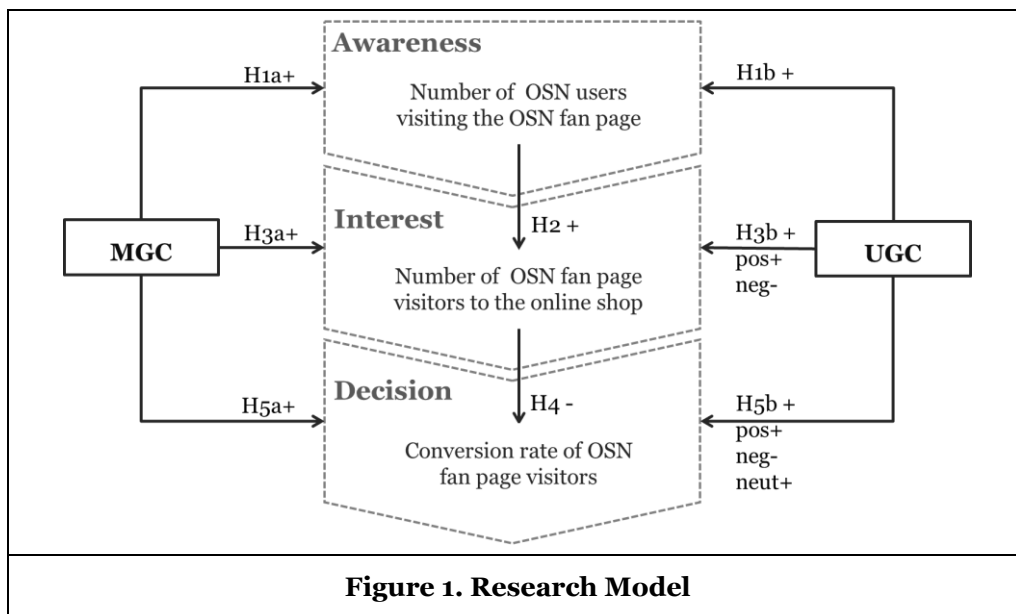
Awareness Creation

MGC on OSN fan pages raises awareness for companies' products (Liu 2006) by appearing in the newsfeeds of all fans (Goh et al. 2013) and by increasing fan page engagement and usage intensity (Jahn and Kunz 2012).

H1a: An increase in MGC volume on a fan page creates awareness among OSN users.

Higher volumes of UGC and broad distribution of UGC increase awareness (e.g., Dhar and Chang 2009; Duan et al. 2008). UGC posted in OSN is displayed on the corporate fan page and distributed by the newsfeed mechanism to all fans of the fan page and to all contacts in the creator's social network (Debatin et al. 2009). Since all UGC is pushed into the newsfeeds, irrespective of whether it is negative, positive, or neutral, UGC valence is of secondary importance in awareness creation. UGC also increases the social interaction value of a fan page and therefore fan page engagement (Jahn and Kunz 2012).

H1b: An increase in UGC volume (irrespective of its valence) on a fan page creates awareness among OSN users.

Interest Stimulation

In the multi-stage purchase decision process as proposed by Bettman (1979) and Shocker et al. (1991), the awareness stage is followed by the interest stage (De Bruyn and Lilien 2008).

H2: An increase in the number of users actively using the fan page stimulates user interest.

Informational cues provided by MGC about characteristics and quality of products (Goh et al. 2013; Lin and Goh 2011) stimulate consumer interest beyond initial attention and prompt them to evaluate the products more closely; for instance, by visiting the online shop where the products are sold.

H3a: An increase in MGC volume stimulates user interest.

Rishika et al. (2013, p. 108) report that "customer participation in a firm's social media efforts leads to an increase in the frequency of customer visits", if UGC is predominantly positive. However, users in OSN also create negative UGC to express their negative experiences and dissatisfaction with products (Lin and Goh 2011; Liu 2006; Yin et al. 2011). Negative product experiences influence attitudes and behavior of other users (Yin et al. 2011) and reduce perceived product quality (Liu 2006). Thus, negative UGC will have adverse effects on consumer interest for a product.

H3b: An increase in the volume of positive (negative) UGC increases (decreases) user interest.

Purchase Decision

Increased interest in a company's products will probably prompt more consumers to visit the online shop where the products are sold. But increased numbers of shop visitors do not necessarily translate into higher conversion rates, i.e. the proportion of web shop visits that lead to a purchase. Moe and Fader (2004) report an instance of visitor numbers declining by over 60% on Amazon.com accompanied by only a 25% decrease in conversion rate. They trace this effect partly back to heterogeneity in visitors' motivations: "some visits are motivated by planned purchases, while others are associated with hedonic browsing (akin to window shopping)" (Moe and Fader 2004, p. 326). Since OSN are mainly hedonic-oriented information systems (Hu et al. 2011; Sledgianowski and Kulviwat 2008), we expect that many visitors attracted via fan pages are engaged in hedonic browsing and that stimulating consumer interest via fan pages will decrease conversion rates.

H4: An increase in the number of users visiting the online shop decreases the conversion rate.

Marketing and advertising information (Ailawadi and Neslin 1998; Manchanda et al. 2006; Zhang and Wedel 2009) as well as persuasion (Meyers-Levy and Malaviya 1999; Russo and Chaxel 2010; Wu et al. 2009) are major drivers of consumer purchase. Posted on fan pages in OSN, MGC may increase the propensity to purchase due to its (typically positive) informational cues (Goh et al. 2013; Rishika et al. 2013) and its persuasiveness (Lin and Goh 2011).

H5a: An increase in MGC volume increases the conversion rate.

Both volume (e.g., Dhar and Chang 2009) and valence (e.g., Chintagunta et al. 2010) of consumer reviews on retailing websites affect sales (e.g., Zhu and Zhang 2010). Valence of UGC also matters in OSN (Goh et al. 2013): apparently, even neutral UGC can have a positive effect on daily sales performance (Sonnier et al. 2011). This may be due to the fact that consumers value information richness in UGC (Goh et al. 2013) and neutral UGC are most likely to contain balanced information ("pros and cons"; Mudambi and Schuff 2010).

H5b: An increase in the volume of positive or neutral (negative) UGC increases (decreases) the conversion rate.

Data Description and Analysis

Data Collection

We tested our hypotheses on data provided by a large German e-tailer for books, movies, music, and computer games. The largest share of revenue can be accounted to books, and the vast majority of items sold are third-party products. The company has a strong presence on Facebook, which is its only marketing channel; no marketing instruments other than MGC were used. The e-tailer provided us with its online shop statistics for customers who accessed the shop through its Facebook fan page between October 1st 2010 and March 30th 2012 (547 days). Data included the number of visitors to the online shop and the number of purchases on a daily basis. We also had access to the internal Facebook fan page statistics, including the number of unique active users on a daily basis. We extracted MGC (wall posts and comments) and UGC (wall posts and comments) from the fan page through the Facebook API, collecting 1,010 MGC items and 5,623 UGC items. Since MGC is generally all positive (Risihika et al. 2013), we did not classify it by sentiment. UGC items were classified as positive, negative, or neutral in sentiment. Table 1 summarizes the means and differences of our observed variables. Although all variables improved with time, standard deviations were very high, indicating that improvements were not persistent.

Table 1. Descriptive Statistics		
Variable	Mean	Standard Deviation
Daily Active Users (DAU) – unique	2,499.827	1,952.241
ΔDAU	27.132	1,803.364
Visits – unique	382.346	196.331
ΔVisits	0.222	163.733
Conversion Rate (CVR) in %	1.864	2.299
ΔCVR in %	0.002	3.082
ΔPositive UGC	4.124	5.704
ΔNeutral UGC	5.191	7.909
ΔNegative UGC	0.914	2.277
ΔMGC	0.906	1.243

For classifying UGR, we used manual rather than automated classification due to the limitations of text mining algorithms in correctly processing textual features like slang, irony, or sarcasm (Stieglitz and Krüger 2011). Classification was carried out by a team of undergraduate students who were all familiar with Facebook. A common understanding of the classification criteria was obtained by giving the students a short tutorial explaining the criteria (as suggested by García-Crespo et al. 2010 and Laros and Steenkamp 2005).

As proposed in prior coding studies (Liu 2006), each item was classified by at least three different students. We may assume reasonably high validity for our classification: for large numbers of items, even classification by only one person yields good results (Chelaru et al. 2012). Items were considered as successfully classified when all three students agreed on the same category. If they did not, other students

re-classified the items until one category led by at least three votes. Our final dataset contains complete public and non-public data for 547 days.

Preliminary Analysis

Our data consist of the number of MGC and UGC per day but not per product. An e-tailer might use MGC to promote one product on day *t*, but UGC created on day *t* may refer to another product promoted several days before. An improvement in the conversion rate on day *t* could be due to UGC on day *t* or to MGC on day *t*. When MGC and UGC refer to different products, MGC (UGC) could thus improve the conversion rate for one product but not for the other. Analysis on the product-level would reveal such effects. The drawback of product-level analysis, however, is that it requires products to be purchased over a reasonable time period. If most of the discussion about a product and most of its purchases happen on the same day it is promoted by the e-tailer, the effect of varying numbers of comments on the dependent variables cannot be determined.

We analyzed the relationship between user comments and wall posts with 7 lag variables for wall posts and comments. User comments on day *t* depend only on e-tailer wall posts on day *t* (p<0.001) and e-tailer comments on day *t-1* (p<0.05).

E-tailer comments on day *t*, on the other hand, depend on e-tailer wall post on day *t* (p<0.001) and user wall posts on day *t* (p<0.01). Wall posts were typically commented on the day they were posted (almost all lag variables are not significant).

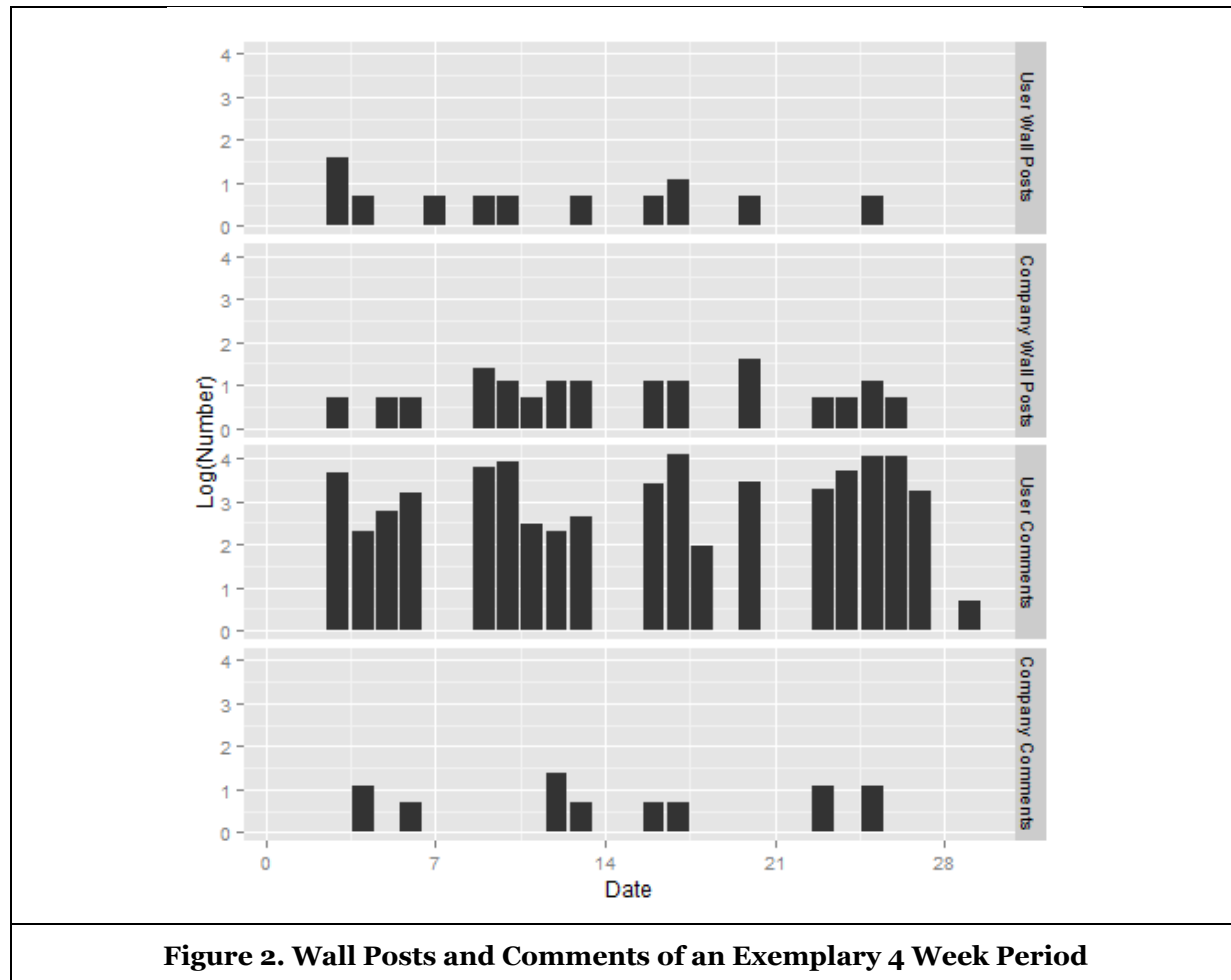Figure 2 illustrates the relationships between wall posts and comments for a randomly chosen period of 4 weeks.

Figure 2. Wall Posts and Comments of an Exemplary 4 Week Period

Table 1 indicates that the e-tailer creates, on average, only one wall post per day. Since one post usually refers to exactly one product[1], we can conclude that most comments on day *t* refer to exactly one product. The products the e-tailer sells are rather homogeneous, which is underlined by the fact that the average price per purchased product is 13.70 Euro with a standard deviation of only 6.07 Euro. Taken in conjunction, the facts that i) the company creates only one post per day, ii) one post typically refers to exactly one product and iii) products are rather homogenous in their price, strongly suggest that the effects of MGC and UGC aggregated at the product level will not differ significantly from the effects of MGC and UGC aggregated on a daily level.

Analysis

We examined the effects of content posted on the fan page on *awareness creation* (the differences in the number of daily active users), *interest stimulation* (the differences in visits to the online shop), and on *purchase decision* (conversion rates[2]). We assume that past behavior predicts future behavior. Augmented Dickey-Fuller tests support this assumption and indicate significance for a lag period of 7 days (p<0.001). We included seven lagged differences of the dependent variables as controls in our models. We used the general method-of-moments first-difference transformation to remove observed but time-stable differences in the content created on fan pages (e.g., UGC with or without user picture) (Ludwig et al. 2013). The three models analyzed in this study are the following:

(1) $\Delta DAU_t = \alpha_1 \Delta DAU_{t-1} + \alpha_2 \Delta DAU_{t-2} + \alpha_3 \Delta DAU_{t-3} + \alpha_4 \Delta DAU_{t-4} + \alpha_5 DAU_{t-5} + \alpha_6 \Delta DAU_{t-6} + \alpha_7 \Delta DAU_{t-7} + \beta \Delta X_t + \Delta u_t,$

(2) $\Delta Visits_t = \alpha_1 \Delta Visits_{t-1} + \alpha_2 \Delta Visits_{t-2} + \alpha_3 \Delta Visits_{t-3} + \alpha_4 \Delta Vistis_{t-4} + \alpha_5 Visits_{t-5} + \alpha_6 \Delta Visits_{t-6} + \alpha_7 \Delta Visits_{t-7} + \beta_1 \Delta DAU_t + \beta_2 \Delta X_t + \Delta u_t,$

(3) $\Delta CVR_t = \alpha_1 \Delta CVR_{t-1} + \alpha_2 \Delta CVR_{t-2} + \alpha_3 \Delta CVR_{t-3} + \alpha_4 \Delta CVR_{t-4} + \alpha_5 CVR_{t-5} + \alpha_6 \Delta CVR_{t-6} + \alpha_7 \Delta CVR_{t-7} + \beta_1 \Delta Visits_t + \beta_2 \Delta X_t + \Delta u_t,$

where

ΔDAU_t	is the difference in the number of unique daily active users from the previous day to the current day *t*;
$\Delta Visits_t$	is the difference in the number of unique visits to the online shop from the previous day to the current day *t*;
ΔCVR_t	is the difference in the conversation rate from the previous day to the current day *t*;
ΔDAU_{t-n}	represents changes in the lagged user behavior from the previous *n* periods;
$\Delta Visits_{t-n}$	represents changes in the lagged visiting behavior from the previous *n* periods;
ΔCVR_{t-n}	represents changes in the lagged conversion behavior from the previous *n* periods;
ΔX_t	represents a matrix of changes in the MGC and UGC variables from the previous day to the current day *t*;
Δu_t	is the change in the random error term from the previous day to the current day *t*; and *t* is the day.

Integrating several lagged differences increases the probability of multicollinearity (Sonnier et al. 2011). However, variance inflation factors (VIFs) below 4 and condition indices (CI) below 7 indicate absence of multicollinearity in all three models.

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[1] Posts which do not refer to a product may contain, for instance, information about e-tailer services (e.g., delivery) or seasonal greetings.

[2] The conversion rate is operationalized as the number of customers who access the shop via the fan page and who ultimately buy one or more products, divided by the number of all customers who access the shop via the fan page.

Results

Awareness Creation – Effects on Active OSN Users

Our results for the first model show that differences in the number of daily active users between any two days affect the differences in the number of daily active users on the following days (ΔDAU_t; Table 2). The effect is negative, which indicates that past increases in daily active users lead to a decrease in the difference between active users on the current day and the previous day (and vice versa). That there is no persistent positive or negative trend is underlined by the fact that ΔDAU_t has a very high standard deviation of 1,803.364 with a mean of 27.132 (Table 1).

Consumer awareness is affected strongly by MGC (Table 2); H1a is supported. Positive and neutral UGC also raise awareness, but negative UGC does not. H1b is partially supported.

Table 2. Results for the Number of Daily Active Users (ΔDAU)		
	Estimate	Std. Error
Intercept	-464.871***	68.253
ΔDAU_{t-1}	-0.772***	0.040
ΔDAU_{t-2}	-0.799***	0.044
ΔDAU_{t-3}	-0.655***	0.046
ΔDAU_{t-4}	-0.621***	0.046
ΔDAU_{t-5}	-0.637***	0.047
ΔDAU_{t-6}	-0.459***	0.045
ΔDAU_{t-7}	-0.035	0.041
$\Delta Positive\ UGC$	36.096**	11.690
$\Delta Neutral\ UGC$	25.942**	7.915
$\Delta Negative\ UGC$	36.728	23.210
ΔMGC	238.401***	45.353
Adj. R²	0.642	

Interest Stimulation – Effects on Visits to Online Shop

Our results for the second model show that differences in the number of visits to the online shop from one day to the next ($\Delta Visits_t$) depend on previous differences in the number of visits to the online shop and on the differences in the number of daily active users (Table 3). H2 is supported. The lagged variables again have a negative effect and indicate that there is no persistent change in $\Delta Visits_t$ over time.

Surprisingly, neither MGC nor UGC affect the differences in the number of visits to the online shop directly; H3a and H3b are not supported. The results for our first model (Table 2), however, indicate an indirect effect on visits: both MGC and UGC influence the differences in the number of daily active users, which in turn influence the differences in the number of visits to the online shop (Table 3).

We also tested for direct effects of MGC and UGC by omitting the differences in the number of daily active users from the second model. The reduced model is inferior to the original model in terms of AIC, BIC, and adjusted R², but shows clearly that MGC and neutral UGC affect the differences in the number of visits to the online shop. We may therefore assume an indirect effect of MGC and UGC on differences in the number of visits to the online shop.

| Table 3. Results for the Number of Visits to the Online Shop (Δ*Visits*)		
	Estimate	Std. Error
Intercept	-12.403	9.083
$\Delta Visits_{t-1}$	-0.318***	0.043
$\Delta Visits_{t-2}$	-0.282***	0.046
$\Delta Visits_{t-3}$	-0.219***	0.046
$\Delta Visits_{t-4}$	-0.194***	0.046
$\Delta Visits_{t-5}$	-0.114*	0.047
$\Delta Visits_{t-6}$	-0.055	0.045
$\Delta Visits_{t-7}$	0.027	0.044
ΔDAU	0.027***	0.004
$\Delta Positive\ UGC$	-0.845	1.535
$\Delta Neutral\ UGC$	1.379	1.057
$\Delta Negative\ UGC$	2.033	3.086
ΔMGC	6.358	6.158
Adj. R^2	0.223	

Purchase Decision – Effects on Conversion Rate

As in the previous two models, negative estimates of the lagged variable indicate that there is no persistent trend over time (here: in ΔCVR_t; Table 4).

Table 4. Results for the Conversion Rate (ΔCVR)		
	Estimate	Std. Error
Intercept	-0.106	0.139
ΔCVR_{t-1}	-0.864***	0.044
ΔCVR_{t-2}	-0.750***	0.057
ΔCVR_{t-3}	-0.593***	0.064
ΔCVR_{t-4}	-0.500***	0.065
ΔCVR_{t-5}	-0.335***	0.064
ΔCVR_{t-6}	-0.252***	0.058
ΔCVR_{t-7}	-0.112*	0.044
$\Delta Visits$	-0.002*	0.001
$\Delta Positive\ UGC$	-0.035	0.025
$\Delta Neutral\ UGC$	0.034*	0.017
$\Delta Negative\ UGC$	0.025	0.050
ΔMGC	0.077	0.095
Adj. R^2	0.433	

Differences between conversion rates are quite low at an average of 0.002 (Table 1). A high increase in the differences in the number of visits to the online shop between the previous day and the current day leads

to a moderate reduction of the differences in conversion rate between the two days. H4 is supported. This indicates that activity on the fan page increases the number of shop visitors who are engaged in hedonic browsing to a greater degree than the number of visitors planning a purchase. Conversely, conversion rates would increase if the number of shop visitors planning a purchase increased to a greater extent than the number of "hedonic browsers". Our results show that the volume of MGC does not affect the conversion rate; H5a is not supported. Neutral UGC has a positive effect on differences in conversion rates, but the effects of positive and negative UGC are not significant. H5b is therefore partially supported.

The results of all three models are summarized in Figure 3. Directly, MGC and UGC influence awareness creation and purchase decisions. Indirectly, they also influence the number of OSN users who visit the online shop from the fan page by increasing the number of active users of the OSN fan page.

Figure 3. Results
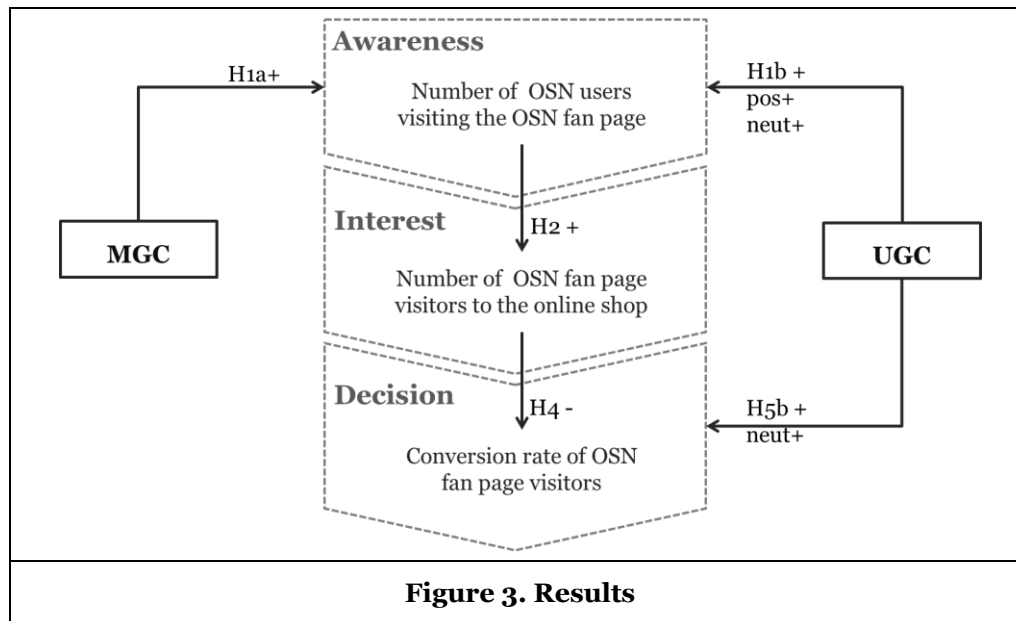
We can now determine how many users must be attracted by the e-tailer in order to achieve a certain increase in sales, and how great an effort (in terms of MGC and UGC creation) will be required. The average conversion rate is 1.864% (Table 1): out of 1000 visitors to the online shop, 18.64 on average will order a product. At a daily average of 382 visitors to the online shop (Table 1), 7.12 customers per day will order one or more products on average.

Consider a situation in which the e-tailer successfully attracts 1,000 additional users. This generates 27 additional visits to the online shop; reduces the conversion rate by 0.054 to 1.810%; and increases the overall number of visitors to the online shop to 409. Out of these 409 customers, 7.40 will purchase one or more products. The effort for attracting 1000 additional users to the fan page is quite reasonable, with approximately 4 MGC posts, 28 positive UGC posts, or 39 neutral UGC posts. Neutral UGCs have the additional advantage of positively affecting the conversion rate.

On an average day, 4.124 positive UGC posts, 5.191 neutral UGC posts, and 0.906 MGC posts are created. This attracts 500 users to the fan page, generates 13.5 visits to the online shop, and improves the conversion rate by 0.149%. Considering that the average conversion rate is 1.864%, the increase is quite substantial.

One, Two or Three Stages

We examine the effects of MGC and UGC on all three stages of the purchase decision process. Prior research mostly focused on the effects of MGC and UGC on final purchase decisions (Goh et al. 2013, Ludwig et al. 2013). We argue that the reduction to a one-stage model will lead to wrong conclusions about the effects of MGC and UCG. A comparison of one-stage, two-stage, and three-stage models

(Table 5) clearly indicates that the three-stage model fits our data best in terms of AIC and BIC. MGC and UGC have an effect on the number of daily active users and only an indirect effect on the number of visits. The model for *ΔVisits* is significantly better when adding *ΔDAU* as an independent variable (Table 5). *ΔVisits* on the other hand has a significant effect on *ΔCVR* and the model for *ΔCVR* improves when adding *ΔVisits* as an independent variable. All three stages have to be considered to correctly estimate the effects of MGC and UGC on *ΔCVR*.

Table 5. Comparison of One-, Two- and Three-Stage Model[3] [Estimates (Standard Error)]						
	One-Stage	Two-Stage		Three-Stage		
	ΔCVR	*ΔVisits*	*ΔCVR*	*ΔDAU*	*ΔVisits*	*ΔCVR*
ΔDAU	-	-	-	-	0.027*** (0.004)	-
ΔVisits	-	-	-0.001* (0.001)	-	-	-0.002* (0.001)
ΔPositive UGC	-0.037 (0.025)	0.098 (1.575)	-0.357 (0.025)	36.096** (11.690)	-0.845 (1.535)	-0.035 (0.025)
ΔNeutral UGC	0.032 (0.017)	2.095 (1.085)	0.034* (0.017)	25.942** (7.915)	1.379 (1.057)	0.034* (0.017)
ΔNegative UGC	0.019 (0.050)	3.139 (3.175)	0.026 (0.050)	36.728 (23.210)	2.033 (3.086)	0.025 (0.050)
ΔMGC	0.071 (0.095)	13.268* (6.263)	0.073 (0.095)	238.401*** (45.353)	6.358 (6.158)	0.077 (0.095)
Adj. R[2]	0.427	0.178	0.433	0.642	0.223	0.433
AIC	2,321.100	6,548.821	2,317.728	8,568.252	6,519.331	2,316.174
BIC	2,376.122	6,603.842	2,400.623	8,623.273	6,578.585	2,375.428

Looking at the one-stage model, one would conclude that neither UGC nor MGC have a significant effect on conversion rate. The indirect effect of MGC on the number of visits to the shop is also hidden. In the two- and three-stage models, the effect of MGC on the number of visits and the direct effect of neutral UGC on the conversion rate become visible. The indirect effect of positive UGC and MGC on conversion rate is only revealed in the three-stage model.

To illustrate how important it is to choose the right model, let us consider their answers to the question whether creating 5 additional MGC posts is a worthwhile undertaking, from the e-tailer's point of view.

The one-stage model shows us that 5 additional MGC posts have no effect on the initial conversion rate of 2%. The two-stage model suggests that the 5 MGC posts lead to 66 new visits, which in turn reduce conversion rate to 1.93%. The three-stage model predicts that the 5 MGC posts will attract 1,192 new active users, increase visits by 32, and reduce conversion rate to 1.94%.

The one-stage model will make the e-tailer question the fundamental usefulness of its OSN activities. The two-stage model misestimates the difference in visits by 100%, giving the e-tailer an overly optimistic estimate of the increase in revenues through OSN activities (computed as $CVR \times Visits \times Average\ Revenue\ per\ Visit$). The three-stage model, finally, explains conversion rate as well as the two-stage model, but performs much better in predicting the number of visits (higher R[2], lower AIC and lower BIC compared to the two-stage model). Using the three-stage model will therefore give the e-tailer more accurate estimates of key business figures (e.g., revenue) and provide greater insight into the effects of marketing activities in OSN on users.

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[3] All models included lagged variables as specified in the three-stage model. For the sake of clarity, however, intercepts and lagged variables are not presented in Table 5.

Discussion and Conclusion

The main aim of our study was to contribute to a deeper understanding how MGC and UGC in OSN affect consumer purchase decisions. We modeled the purchase decision process as a multi-stage process of awareness creation, interest stimulation, and final purchase decision (Shocker et al. 1991). This perspective is new to research on MGC and UGC in OSN and their effect on sales. Our study provides new insights into the dynamics of company and customer interaction through OSN.

By combining OSN and company data, we were able to observe intermediate stages in the purchase decision process (Shocker et al. 1991) and to separate the effects of MGC and UGC on each stage. We were thus able to provide evidence that i) the three-stage model is superior to both one- and two-stage models, that ii) creating awareness in OSN does not necessarily increase sales, and that iii) UGC valence plays a major role in consumer purchase decisions.

Our main contribution to current research on consumer behavior in OSN, modeling purchase decisions as the outcome of a three-stage process, holds important implications for future research. Our results indicate that using one- or two-stage models may lead to erroneous conclusions about the effects on MGC and UGC on sales. Specifically, the importance of MGC and UGC in creating awareness and stimulating interest is likely to be underestimated because these effects are hidden in one-stage models.

Second, our study is of particular interest to practitioners: we provide a new perspective for increasing the effectiveness of OSN promotions. Our results indicate that the strongest lever for creating product or service awareness is MGC: frequent postings attract more users to the OSN fan page. Positive and neutral UGC have the same, but weaker, effects. User interest is stimulated indirectly by MGC and UGC: higher numbers of active users on the fan page also increase the number of visits to the online shop. The conversion rate, however, is unaffected by MGC; only neutral UGC succeed in creating a higher conversion rate.

Third, our results provide additional evidence that UGC valence matters, supporting previous results from research on customer reviews (e.g., Mudambi and Schuff 2010) and OSN (e.g., Sonnier et al. 2011). Our study supports Sonnier et al.'s (2011) findings on neutral UGC: they identified a positive effect on conversion rate. In line with Goh et al. (2013) and Mudambi and Schuff (2010), we suggest that neutral (balanced) UGC are richest in information and therefore most helpful for consumers; Ludwig et al. (2013) indeed found that helpful reviews have a positive effect on conversion rates. Prior results on the effect of negative and positive UGC are mixed, however: while Sonnier et al. (2011) report positive UGC to have the greatest effect on sales, other studies find that negative UGC have a greater effect (e.g., Yin et al. 2011). In our data, neither positive nor negative UGC had a direct effect on conversion rate. One possible reason for these mixed results is the use of one-stage models in prior studies. Another possible reason, in particular with regard to Sonnier et al.'s (2011) results, is that both their and our study are based on one company's data only. More research is needed to reconcile these findings.

Our study is subject to some limitations which leave room for further research. First, this study should be expanded beyond the scope of one company in order to find out whether the observed effects can be confirmed for other companies and their "fans". Extending the analysis to companies which use additional marketing channels beside OSN could provide particularly interesting insights into the relative profitability of OSN marketing. Second, we considered the sentiment of UGC (positive, neutral, and negative) and MGC (which has been found to be all positive), but we have not yet investigated other qualitative characteristic like information richness and their effects on the purchase decision process. Third, the second (interest) and third (final decision) stages of the purchase decision process might depend on specific product (e.g., price) and shop (e.g., availability, usability) characteristics. However, the company analyzed in this study operates in Germany, where prices for books are fixed. In addition, we found small variance in prices, indicating that relatively homogenous products were on offer. Future research could build on our findings by extending the analysis to the product level to further refine our understanding of how UGC and MGC on OSN fan pages affect purchase decisions. Another interesting possibility for future research lies in analyzing individual consumer data instead of aggregated data to investigate the effects of MGC and UGC in OSN on individual purchase decision processes. Thus further insights, for instance regarding the influence of individual user characteristics (e.g., age, experience with OSN), could be derived.

Despite these limitations, our study contributes to research on consumer behavior in OSN, specifically with respect to their reactions to MGC and UGC created on fan pages in OSN. By introducing a multi-stage model of consumer decision-making, our study leads to a better understanding of the effects of MGC and UGC on purchasing decision processes.

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