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From Marketer-Generated Content to User-Generated Content: Evidence from Online Health Communities

Completed Research Paper

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Abstract

How should marketers engage with social media features in online communities to shape knowledge contributions from customers in their potential markets? This is an important question because customer contributions are important drivers of business value. We examine the effect of marketer-generated content in online health communities on user-generated content, using longitudinal data from a leading online health community. We focus on the firm's practice of knowledge investment, in which its marketers provide product information or share life experience by posting in the social interaction section of online health platforms. The results demonstrate that because of knowledge investment in healthcare markets, the use of platform's social media feature by marketer influence both the quantity and linguistics features of customer-generated content.

Keywords: Marketer-generated content, user-generated content, online health

Introduction

Social media becomes incredibly popular in recent years. The Pew Research Center reports that 68 percent of USA adults use Facebook, and roughly 73 percent of adults in the USA use two or more social media platforms (Smith; and Anderson 2018). Social media has attracted not only individuals wishing to interact, but also marketers trying to reach those individuals online. The increasingly pervasive use of social media has greatly transformed how firms organize their online marketing activities (Aral and Walker 2011). Firms are continuously using social media to market their brands and products, and interacting with consumers. Firms have adopted various types of social media technologies to influence consumers' purchase intention by creating online word-of-mouth, which can simultaneously consumer-generated content decrease quality uncertainty and increase product awareness (Aral and Walker 2011; Dellarocas 2003). Obviously, social media is becoming a useful tool for firms to engage with customers, and positively influence their perception of firms or firms' products.

Social media platforms, such as Facebook, Twitter, and Microblog, allow firms to register on the firm homepage, and provide interaction between customers and firms. However, in addition to social platforms that allow firms to interact with customers, professional sites such as Amazon (shopping website), Qunar (travel website), and Soyoung (medical website) also launched social features for firm marketers that allow them to strengthen contact with consumers using their digital platforms. In this paper, we examine the impact of the adoption of the firms' marketer-generated content (MGC) feature on consumer-generated content measures in a systematic fashion. We also provide insights for researchers and practitioners as to situations in which firms should spend time and resources embracing the new online social features supported through online health sites to remain competitive.

Firms' marketer-generated content means that marketers use social interaction features to generate content on behalf of the firm to engage consumers actively (Goh et al. 2013). Prior literature has mainly focused on the impact of MGC on consumers' purchase behavior (Goh et al. 2013; Kumar et al. 2016; Scholz et al. 2018), customer engagement (Lee et al. 2018; Yang et al. 2019), and firms' performance (Gong et al. 2017; Song et al. 2019). However, the effects of firms' MGC on UGC have not been well understood. UGC refers to publically visible online content initiated, created, circulated and consumed by users (Kim and Johnson 2016). Previous research has shown that UGC positively influences firms' sales (Chintagunta et al. 2010; Moe and Trusov 2011; Zhu and Zhang 2010), customer engagement (Yang et al. 2019), and consumers' consumption intention (Yi et al. 2019). Thus, firms are committed to encouraging users to generate more content (Yang et al. 2019). Yet little is known about the influence mechanism of MGC on professional sites on the quantity and linguistics features of user-generated content.

To systematically bridge this research gap, we begin by asking our first research question: (1) What is the impact of MGC on the quantity of consumer-generated content on online health platforms? Despite the firm's research on social media marketing has made significant progress (Chen et al. 2012; Porter and Donthu 2008), there are debates about whether firm marketers should take a proactive role in using social features to influence community member behaviors in online professional platforms. Some researchers argue that firms' effort is essential to stimulate member contribution, and firms' effort can encourage users to contribute high-quality content (Porter and Donthu 2008; Porter et al. 2011). We extend prior work by arguing that a special form of firms' effort, namely, marketer-generated content comes from firms embracing social feature, is likely to stimulate user-generated content in online health platforms. And this relationship the need for empirical evidence to shed light on the effectiveness of firms' marketer-generated content to nurture their consumers.

More specifically, in our data, we can observe the introduction of a new social feature allowing marketers to post and share experiences like other users in an online health platform. The launch of a new social feature may benefit those medical institutions in the online health platform that embrace the new social feature to engage with their consumers. However, an empirical challenge lies in establishing the causal effect of MGC (i.e., medical institutions' marketers posts) on the quantity of consumer generated content because the decision to adopt social feature to interact with consumers is endogenous (self-selected). The medical institutions that adopt the social feature and post content like consumers might be systematically different from the medical institutions that choose not. Without addressing the self-selection of a medical institution's decision to publish content like other users, the estimation of the effect of marketer generated content would be biased. Using several causal identification strategies, our study is the first to provide an empirically driven, comprehensive understanding of the unique situations in which medical institutions should spend time and resources to embrace the new social features.

MGC not only affect the quantity of consumer generated content, but also the linguistics features of consumer generated content. Past literature has not examined the relationship between MGC and the linguistics features of consumer generated content, which is our second research question: (2) What is the impact of marketer generated content on the linguistics features of consumer generated content in online health communities? As the importance of text information escalating in the current social media context, many researchers began to pay attention to the linguistics features of consumer generated content (Goh et al. 2013). The linguistics features of review contents positively affected sales (Ghose and Han 2011). Data collection design choices (Lukyanenko et al. 2019), smartphone use (Melumad et al. 2019), and negative service experience (Presi et al. 2014) affected consumer generated content. However, few researches studied the factors that influence the linguistics features of UGC. Moreover, the role of MGC in influencing the linguistics features of consumer generated content has not been investigated. As an "engine", MGC tried to "engineer" content among customers, which means MGC may be characterized as being firm initiated but consumer implemented(Godes and Mayzlin 2009). To advance our understanding, we examine how MGC affects linguistics features of consumer generated content.

In addition, we also explore questions: (3) How do returns on MGC vary over time? (4) How do returns on MGC vary over geography? We find temporal and geographical variations in the returns on medical institutions' knowledge investment. The return on medical institutions' knowledge investment, in terms of the amount of consumer-generated content it stimulates, increases with the age of the medical institutions. In addition, when we examine the moderating effects of geography on the relationship between medical institutions' MGC and UGC, our analyses reveal that MGC varies returns across different cities. Specifically, greater returns are realized when MGC is made in cities with more internet search behavior.

Literature Review and Hypotheses

Literature Review

The studies of MGC and UGC have evinced keen interest in research because of a rapid increase in digital content in the past decade. Our study is related to three different research streams: (1) marketer-generated content, (2) user-generated content, and (3) online health communities. Our work extends prior research on MGC and UGC, which has primarily focused on the social media context, to the context of online healthcare. Furthermore, our study examines the process from MGC to UGC in online health platforms, thus filling a gap in e-healthcare literature.

Marketer-Generated Content

With the development of social media, marketer generated content is increasingly popular on social media platforms (Meire et al. 2019). MGC is marketer initiated marketing communications, and marketers, on behalf of their firms, can broadcast a wide variety of messages to a large number of consumers (Kumar et al. 2016; Lee et al. 2019). MGC, as an authoritative information source, could inform consumers of products or services and influence consumer behavior (Kumar et al. 2016). And researchers began to investigate firms that adopted social media to generate content related to their brands or products and to interact with their consumers. Prior literature explored the effects of firms' marketer-generated content on consumer behavior and firms' performance. For instance, Kumar et al. empirically studied the effects of firm-generated content in social media on customer behavior using large specialty retailer data. They found that after accounting for the effects of television advertising and email marketing, firm-generated content has a positive and significant effect on consumer spending, cross-buying behavior and consumer profitability (Kumar et al. 2016). Goh et al. quantified impact of both MGC and UGC on consumers' apparel purchase expenditures, and found that UGC exhibits a stronger impact than MGC on consumer purchase behavior, and social media content affects consumer purchase behavior through embedded information and persuasion (Goh et al. 2013). Lee et al. coded 106,316 Facebook messages across 782 companies to study the association of marketing content with user engagement (likes, comments, shares) with the messages. They found that firm-generated content related to brand personalities, like messages with humor and emotion, is associated with high levels of consumer engagement. However, firm-generated content related to deals and promotions is associated with low levels of consumer engagement (Lee et al. 2018).

In terms of firms' performance, including firms' sales and revenue, Gong et al. conducted an experimental study to test whether and how tweeting affects product sales (i.e., TV shows) and found that firms' tweets directly boost viewing, whereas influential retweets increase viewing (Gong et al. 2017). Song et al. build a prediction model to explore the effects of UGC as well as MGC on a microblogging platform and UGC on the third-party platform on movie box office revenue. The empirical results showed that volume of MGC directly predicts box office revenue (Song et al. 2019). Zhao et al. explore the impact of MGC and UGC on view count of a free fitness video, and found that normative and social UGC are positively associated with online fitness videos' view count increase(Zhao et al. 2022). An extensive body of literature on MGC tends to focus on impacts of MGC on consumer behavior or product sales. Our study differs from the above studies by focusing on the impact of MGC on the quantity and linguistics features of UGC in online health communities.

User-Generated Content

Most studies have begun to examine the value of customers' social media contributions to firms (Meire et al. 2019). UGC is the main form of customers' social media contributions. UGC, such as online review (Goh et al. 2013), Usenet newsgroup conversations (Godes and Mayzlin 2009), internet postings (Tumarkin and Whitelaw 2001), blog postings (Dhar and Chang 2009), tweets (Rui et al. 2013), and user-created magazines (Albuquerque et al. 2012), refers to information that consumers generate in online platforms to regularly share their experiences (Tirunillai and Tellis 2012). UGC is available quickly and the firms se UGC at a low cost (Timoshenko and Hauser 2019). And firms are also consuming UGC for their own purpose. UGC is critical for firms for a number of reasons. First, the rapid development of Web 2.0 allows online platforms to aggregate positive, negative, and neutral word of mouth from consumers, which is perceived as trustable by potential customers (Mudambi and Schuff 2010). Second, the firms and customers of online platform do not know each other, thus, there is information asymmetry between them, leading to market inefficiencies and prohibiting the realization of transaction. UGC in online platforms can reduce information asymmetry between firms and customers. Third, the volume of UGC positively affects sales of most products, such as books (Chevalier and Mayzlin 2006), movies (Chintagunta et al. 2010; Duan; et al. 2008), video games (Zhu and Zhang 2010), and music (Dhar and Chang 2009).

Researchers studied the impact of UGC on product sales (Chintagunta et al. 2010; GÖZEGİR and GÖÇER 2018; Moe and Trusov 2011; Zhu and Zhang 2010), customer engagement (Yang et al. 2019), users content usage behavior (Ghose and Han 2011), consumers' consumption intention (Yi et al. 2019), and hospital reputational dynamics (Ivanov and Sharman 2018). Some literature explored UGC as a large-scale corpus, extracting features from UGC to identify consumer needs (Timoshenko and Hauser 2019) and early adverse event warnings (Abbasi et al. 2019). However, the research of the influencing factors of UGC is limited. Only Lukyanenko et al. conduct an experimental study to examine the effects of data collection design choices on the quality of crowdsourced UGC. They found that instance-based data collection results in high accuracy, dataset completeness, and number of discoveries, but this comes at the expense of lower precision in crowdsourced UGC (Lukyanenko et al. 2019). Although researchers and practitioners are aware of the importance of UGC to firms, there is no literature to explore how marketers drive UGC.

MGC & UGC in Online Health Communities Context

Prior literature studied MGC and UGC on social media such as Facebook, Twitter, Sina. In this paper, we argue that MGC and UGC on online health platforms are conceptually different from MGC or UGC on social media in several ways, such as purpose, source, audience, and potential effects on consumers.

First of all, the two types of MGC are generated by different purposes. MGC on social media has a vigorous commercial purpose, and firms use social media as a marketing tool to promote their products or services (Kumar et al. 2016). MGC on online health platforms is more anthropomorphic, and the purpose of marketer's postings is to get closer to customers. Marketers also share popular science contents rather than solely commercial ones related to products or services. Second, the two types of UGC are generated by different sources. Users who generate content in social media can be divided into two categories, consumers who had purchased products or services and users without purchasing experience can comment on MGC (Yang et al. 2019). In online health platforms, for users with purchase experience, they can comment on MGC and at the same time generate post-operative diaries to record their recovery. Diaries contain more content than comments. Third, the audience of MGC on online health platforms may differ from the audiences of MGC on social media. Given that the MGC audience on social media is users who use social media applications, and some users who adopt social media may just want to connect with other individuals, not with the firms, a large proportion of platform users may not be interested in the firm's industry. The MGC audience on the online health platform is targeted, and the users who use the online health platform are those who have needs for health or care about health. Forth, the two types of MGC have different effects. For MGC on social media, because the social platform where the MGC is not consistent with the place where consumers purchase, MGC on social media indirectly affects potential consumers' behavior. For MGC on online health platforms, MGC, consumer purchase behavior, and UGC can all be performed on online health platform, thereby reducing consumer transaction costs, MGC on online health platform directly affect consumers. Therefore, in this study, we focus on MGC and UCG in online health platforms, and how MGC become a powerful diving force for UGC. MGC on online health platforms is also different from the MGC on the open source knowledge sharing platform. The MGC of the open source platform pays more attention to the sharing and dissemination of professional knowledge, and the commercial purpose is weaker than that of the online healthy MGC. Second, the two types of UGC are produced by different sources. In the open source platform, any user can comment on MGC (Yang et al. 2019). On the online health platform, only users with purchasing experience can respond to MGC and generate a postoperative diary, which contains more content than comments. Third, the two types of MGC have different effects. For MGC on open source, the provider of MGC usually conducts after-sales management in the platform. For the MGC on the online health platform, it is more about the pre-sales intervention of the content provider to the customer, which directly affects the consumer. To sum up, from the perspective of commercial purposes, the MGC of online health platforms is between the MGC of social media and the MGC of open source platforms. In terms of form and content, the UGC of the online health platform is displayed in the form of a diary, which contains more abundant content, compared with the other two types of platforms.

Hypotheses

We formally develop a series of hypotheses on MGC and UGC. Our study draws on marketing, information system, sociology theories to investigate MGC and UGC. More specifically, we examine the impact of MGC on quantity and linguistics features of UGC. And how returns on MGC vary by time and geography.

Marketer-generated Content and User-generated Content Quantity

Prior literature proposed that efforts from firms are a critical determinant of online community success, and Huang et al. argued that firms' effort stimulate greater user contribution to the open knowledge community (Huang et al. 2018). We extend prior work by suggesting that a particular form of firms' effort——namely, MGC, as a knowledge investment, or knowledge seeding——is likely to stimulate UGC for firms in online health platform. Prior research suggests that the effectiveness of knowledge exchange is influenced by sociologically-driven pro-social motives and organizational norms (Nambisan and Baron 2010). According social norms theory, the norms emphasize a moral obligation toward others, arguing that actions taken by one party in an exchange relationship often result in reciprocated actions by another party (Jarvenpaa and Leidner 1998). Firms' benevolent actions toward consumers may lead to a sense of moral obligation on the consumer's part such that they will perform an act of reciprocity to restore equality in the relationship with the firm (De Wulf et al. 2001). In online health platforms, medical institutions demonstrate that it genuinely cares about the well-being of the consumers by sharing valuable professional health knowledge in the public domain, and making customers feel benevolence of medical providers (Thon and Jucks 2017). This, in turn, leads to consumers increased willingness to create value for the medical institution by sharing their own knowledge (Huang et al. 2018). Therefore, we propose that firms' knowledge investment (i.e., MGC) will increase consumers' propensity to generate content, we hypothesize :

H1: Marketer-generated content positively affects the volume of user-generated content in online health platforms.

Marketer-generated Content and User-generated Content Linguistics Features

MGC also has effects on linguistics features of UGC. The prior literature shown that a firm's knowledge investments are likely to facilitate the diffusion of knowledge related to its products and services, thereby enhancing the body of knowledge the potential consumers possess (Huang et al. 2018). Prior literature found that when firms make knowledge investments, users can associate the firms' knowledge with their own experience and generate new ideas, and thereby improving users' capacity to contribute knowledge (Benbya and Van Alstyne 2011). When consumers have a higher contribution capacity, the content they generate will contain rich information and express the content in various forms. Moreover, Porter et al. found that firms' effort is effective in encouraging users to contribute high-quality content (Porter et al. 2011). In online health communities, MGC, as a kind of knowledge investments, are likely to promote users' capacity to generate content. And consumer contribution capacity leads to the improvement of UGC. Hence, we hypothesize:

H2: Marketer-generated content positively affects the linguistics features of user-generated content (i.e., user-generated content with length, user-generated content with emotion, and user-generated content with video) in online health platforms.

How Returns on Marketer-generated Content Vary over Time

Although we argued in the previous section for a positive return on MGC in terms of the quantity and linguistics features of UGC it simulates, we also expect a temporal variation in the returns on MGC. For long-established firms, the rise of digital platforms is transforming their traditional offline marketing. Long-established firms have rich marketing experience. Compared with firms that have been established for a short time, long-established firms are more aware of the importance of online marketing, and these firms have more energy for online activities because the firms have a customer base and a sound operating system. Additionally, long-established firms have rich marketing experience and understand the needs of customers better, so these firms' MGC is closer to customers and can better stimulate UGC. Thus, we hypothesize:

H3: In online health platforms, the age of the medical institutions positively moderates the return on market-generated content (i.e., the positive effect of marketer-generated content on stimulating average user-generated content is greater when the medical institution has been established for a long time)

How Returns on Marketer-generated Content Vary over Geography

We also expect a variation in the returns on MGC due to different users have different knowledge absorptive capacity in the communities. Research on interorganizational knowledge transfer suggests that the absorptive capacity affects the degree to which knowledge is successfully transferred from the source to the recipient (Alavi and Leidner 2001; Szulanski 1996). Empirically, studies conducted in the context of enterprise software show that the transfer of enterprise resource planning-related knowledge from consultants to their clients is greatly influenced by the clients' absorptive capacity (Ko et al. 2005; Xu and Ma 2008). Huang et al. suggest that the transfer of knowledge from community sponsor to community members is impacted by community members' absorptive capacity (Huang et al. 2018).

Applying this line of logic to our context of study, we propose that when firm marketers generate content, the absorptive capacity is possessed to various degrees by consumers from different cities because they have different online search behavior. In particular, the context in this paper is a leading plastic surgery and beauty website, and the target group is mainly the user base who has the spending power and wants to become beautiful. Thus, the consumers from a city with more online search behavior is likely to have a greater absorptive capacity because consumers from these cities browse and read more health-related knowledge online. And these consumers will be better at recognizing, assimilating and using new knowledge, resulting in a higher knowledge contribution capacity of themselves (Huang et al. 2018). When medical institutions generate content, for consumers, with high absorptive capacity, may generate more content. Accordingly, we hypothesize:

H4: In online health platforms, the location of the medical institutions positively moderates the return on market-generated content (i.e., positive effect of marketer-generated content on stimulating average user-generated content is greater when medical institution is located in a city with more online search behavior)

Data Description and Empirical Model

Background

We collected data from Soyoung, the largest online medical plastic surgery platform (www.soyoung.com) in China that connects medical institutions with consumers much like Yelp connects restaurants with consumers. The website was founded in 2013 as an online health platform. At present, the website had more than 7,000 medical institutions and 25,814 qualified doctors. More than 25 million users have left a search and consumption footprint on the platform. And consumers on the platform generated 3.5 million diaries. The site allows users to search for medical institutions by country location, specialty, institutes' type, number of doctors in medical institutes, and institutes' age. Search results contain an overview of each institution and a link to the home page, address, strengths, qualifications, ratings, and quantity of UGC.

The platform launched a new feature allowing medical institutions to post, which can be displayed on the institution's homepage and platform social sections, in October 2013. This feature allows medical institutions to directly interact with all users. The post contents are displayed on the platform's social sector and are publicly viewable by all users reading the post.

Data Description

In this study, we use a panel data set of a 26-month period (pre- and post- medical institution post feature adopt) at the medical institution level from the medical platform. We have collected the full history of institutions' information, including institutions' name, postings, consumers' ratings, and consumers' diaries. In Table 1, we provide the summary statistics for some of the key variables used in this study. Our data set has a total of 758 medical institutions with 219,716 postings. The time span of our study is from May 2017 to December 2018. The adoption of post feature enables a quasi-experiment to examine the effect of MGC. We therefore employ difference-in-difference (DID) method to quantify this impact, by examining pre- to post- user-generated content difference between the adoption and non-adoption of post feature for medical institutions. To deal with self-selection problem, we use propensity score matching (PSM) and look ahead propensity score matching (LA-PSM) to deal with hidden bias problems due to latent variables.

Variables	Description	Min	Mean	Max	SD
NCD	Number of customer diaries	0	30.749	1367	66.574
NDL	Number of customer diaries belonging to long text	0	6.745	425	20.116
NDE	Number of customer diaries with emotion	0	0.822	188	3.198
NDV	Number of customer diaries with video	0	0.197	35	0.914
NRR	Number of responses to reviews	0	7.137	2258	41.121
NLR	Number of like to reviews	0	526.766	105047	3263.114
NBR	Number of browse to reviews	12	273034.1	3.40e+07	888363
NRD	Number of responses to diary	0	439.610	135173	3757.31
NLD	Number of like to diary	0	309.591	95087	2465.473
NBD	Number of browse to diary	0	34523.22	5880000	185635.7
DPL	Diary publisher level	0	0.0068	3	0.103

Table 1. Descriptive Statistics

Measures

Dependent Variables. We measure the UGC using four variables: NCD_{it}, NDL_{it}, NDV_{it}, and NDE_{it}. NCD_{it} is the number of customer diary of institution i in time period t, and measures the number of UGC. The linguistics features of UGC measured by NDL_{it}, NDV_{it}, and NDE_{it} (Manganari and Dimara 2017; Yazdani et al. 2018). NDL_{it} refers to the number of the customer diary of institution i in time period t with a long text (long text with more than 100 characters). NDE_{it} is the number of customer diary with emotion of institution i in time period t. NDV_{it} refers to the number of customer diary with video of institution i in time period t.

Independent Variables. Our key independent variables are whether firms' marketers post MGC. Specifically, $TreatmentGroup_i$ equal to 1, which means the medical institution i adopted the posting feature; otherwise, the value of the $TreatmentGroup_i$ variable is 0. Meanwhile, if the $PostTreatment_{it}$ variable value is 1, the month t denotes a month on and after medical institution i adopts the feature; alternatively, the value of the $PostTreatment_{it}$ variable is 0.

Moderator Variables. We use the establishment time of medical institutions and medical institutions' location as moderator variables. Age_i refers to medical institution $i's$ establishment days. $City_i$ is the city of medical institution i. Baidu Index (http://index.baidu.com) is a data analysis platform based on user online search behavior. Baidu Index measures the search scale and trend of certain keywords through Baidu search engine. And it can also reflect the geographical distribution of Internet users who pay attention to these keywords. We use Baidu Index to measure the online search behavior of the website name in different cities.

During the study period, the users who searched for the website name the most were distributed in the ten regions as shown in Figure 4. $City_i$ equals 1 when medical institution i is located in the cities in Figure 1, otherwise is 0.

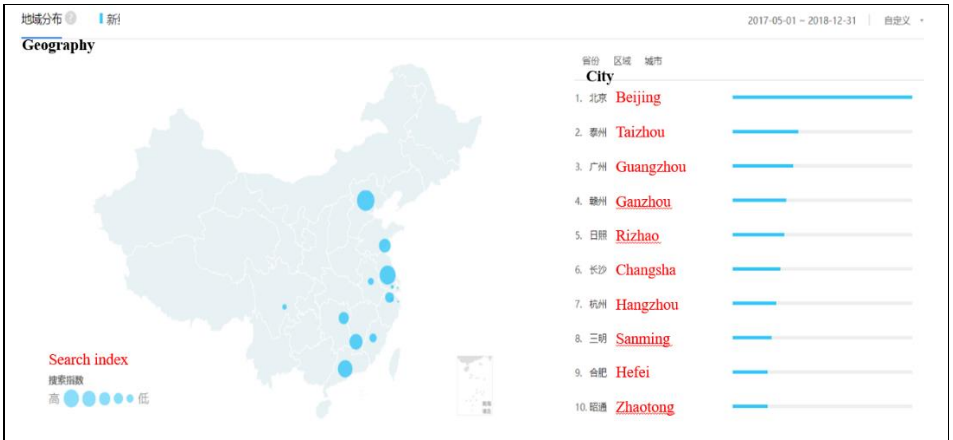

Figure 1. (Color online) Geographical Distribution of Users with the Most Search of the Website Name

Control Variables. We consider the users' evaluation behavior of medical institutions and the interaction behavior of UGC as control variables. Specifically, NRR_{it} refers to the number of user's responses to reviews received by medical institution i in month t. NLR_{it} refers to the number of user's like to reviews received by medical institution i in month t. NBR_{it} refers to the number of user's browse to reviews received by medical institution i in month t. Users' interaction behavior of UGC includes the following variables. NRD_{it} refers to the number of user's responses to diaries received by medical institution i in the month t. NLD_{it} refers to the number of user's like to diaries received by medical institution i in the month t. NBD_{it} refers to the number of user's browse to diaries received by medical institution i in the month t. And DLP_{it} is diary publisher i*'s* level the number of user's browse to reviews received by medical institution i in month t.

Empirical Model

Following Tucker and Zhang (Tucker & Zhang, 2011), we user DID specification with panel fixed effects:

$$Y_{it} = \beta_0 + \beta_1 PostTreatment_{it} + \beta_2(PostTreatment_{it} \times TreatmentGroup_i) + \beta_3 TreatmentGroup_i + \beta_4 Controls + \alpha_i + \varepsilon_{it} \quad (1)$$

Where the dependent variableY_{it}, includes NCD_{it}, NDL_{it}, NDV_{it}, and NDE_{it}. We performed a logarithmic transformation of all dependent variables. $TreatmentGroup_i$ is binary variable indicating whether medical institution i post on social sector of the platform during the study (0: no post; 1: post). $PostTreatment_{it}$ variable equals 1 if month t denotes a month on and after medical institution i adopts the feature; alternatively, the variable is 0. And α_i is the fixed effect.

The estimation results for regression Equation (1) are presented in Table 2. Column (1) - (4) report the results based on OLS regression combine with DID, and the coefficients of the interaction term are significantly positive. $PostTreatment_{it}$ drops from the regressions because its value is similar to interaction term. Column (5) – (8) of Table 2 report the results based on FE regression combine with DID, and the coefficients of the interaction term are also significantly positive. The variable $TreatmentGroup_i$ drops from the regression because its value does not vary with time. We find that after the adoption of the feature of medical institution post, the quantity and linguistics features of customer-generated content about the institutions have more improve than before. The number of customer diary increases 37.7%, the number of customer diary with length increases 25.1%, the number of customer diary with emotion increases 4.6%, and the number of customer diary with video increases 2%.

	DID+OLS				DID+FE			
	(1)NCD	(2)NDL	(3)NDE	(4)NDV	(5)NCD	(6)NDL	(7)NDE	(8)NDV

PostTreatment×TreatmentGroup	0.3874*** (0.0407)	0.2476*** (0.0303)	0.0569*** (0.0174)	0.0270*** (0.0097)	0.3768*** (0.0410)	0.2515*** (0.0308)	0.0456** (.018)	0.0201* (0.0105)
TreatmentGroup	0.2663*** (0.0956)	0.1946*** (0.0612)	0.0631** (0.0255)	0.0164 (0.0115)	----	----	----	-----
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.3151*** (0.1045)	0.6183*** (0.0723)	0.3350*** (0.0371)	0.0360* (0.0199)	1.6239*** (0.0687)	0.8155*** (0.0515)	0.3985*** (0.0305)	0.0476*** (0.0176)
Observations	9367	9367	9367	9367	9367	9367	9367	9367
R-squared	0.1523	0.1458	0.0667	0.1009	0.1471	0.1378	0.0593	0.0931

Table 2. The impact of MGC on UGC

Our findings imply that, in general, the adoption of the feature of medical institution post can improve the quantity and linguistics features of UGC. This means that medical institutions publish content to customers, which is conducive to the increase in customer-generated content.

Causal Identification Strategies in Addressing Endogeneity

To address different endogeneity mechanisms of self-selected post, we use various identification strategies. We have three cases with different identification assumptions: (1) the selection process is driven by observable characteristics, and the differences between control and treatment groups caused by the observable characteristics are stable over time in their influence on customer-generated content (time-invariant shock), (2) the selection process is driven by observable characteristics, and the differences between control and treatment groups caused by the observable characteristics are change over time in their influence on customer-generated content (time-variant shock), and (3) the selection process is driven by unobservable characteristics which change over time in their influence on customer-generated content (time-variant shock)

DID Combine with PSM

Following Goh et al., we consider a DID model combined with PSM (Goh et al. 2013). First, we create a "proper" control group for treated doctors by using PSM. We ensure that the control and treated groups are comparable in terms of observable characteristics. Then we run the DID regression Equation (1).

The results of DID combine with static PSM or dynamic PSM are presented in Table 3. The column (1) and column (5) show that the number of customer diary increases when medical institutions marketers generate content. MGC positively significant impact the number of diary with length, and a 16.7% increase in the number of diary with length. In column (7), the result show that the coefficient on $PostTreatment_{it} \times TreatmentGroup_i$ is significantly positive. However, in terms of the number of diary with video, the results of the coefficient on interactive item are not significant.

	DID + Static PSM				DID + Dynamic PSM			
	(1)NCD	(2)NDL	(3)NDE	(4)NDV	(5)NCD	(6)NDL	(7)NDE	(8)NDV
PostTreatment×TreatmentGroup	0.3362*** (0.0843)	0.3170*** (0.0596)	-0.0240 (0.0395)	0.0256 (0.0241)	0.2691*** (0.0538)	0.1671*** (0.0399)	0.0456** (0.0229)	0.0027 (0.0127)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.5391*** (0.0955)	0.7789*** (0.0675)	0.3404*** (0.045)	0.0484* (0.0273)	1.4137*** (0.1034)	0.7752*** (0.0767)	0.3193*** (0.0440)	0.0153 (0.0245)
Observations	2,136	2,136	2,136	2,136	6,002	6,002	6,002	6,002
R-squared	0.1239	0.1439	0.0580	0.1109	0.1662	0.1572	0.0781	0.1046

Table 3. Addressing Endogeneity Concerns of Self-Selected Post

A Quasi-Experimental Design (DID Combined with LA-PSM)

To account for unobserved characteristics as best as we can, we adopt the LA-PSM method proposed by (Jung et al. 2019) to identify the better control group, and then we combine it with DID approach. Samples are matched using two types of LA-PSM, namely, static LA-PSM and dynamic LA-PSM. In static LA-PSM, first, we focus on a group of institutions that use a post feature in the period between May 2017 and December 2018. We match each of these institutions in the treatment group to an institution that not use post feature in this 20-month period, but that actually adopt post feature between January 2019 and June 2019. We also implement a dynamic LA-PSM approach. As shown in Table 4, the results are consistent with those in the DID + PSM models.

	DID + Static LAPSM				DID + Dynamic LAPSM			
	(1) NCD	(2) NDL	(3) NDE	(4) NDV	(5) NCD	(6) NDL	(7) NDE	(8)NDV
PostTreatment×TreatmentGroup	0.3568*** (0.0926)	0.3351*** (0.0682)	0.0399 (0.0450)	0.0538** (0.0269)	0.1937*** (0.0614)	0.1138** (0.0469)	0.0488* (0.0265)	0.0023 (0.0149)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.5914*** (0.1101)	0.7714*** (0.0811)	0.3863*** (0.0535)	0.0595* (0.0320)	1.4637*** (0.1309)	0.7642*** (0.1001)	0.3579*** (0.0565)	0.0197 (0.0319)
Observations	1,548	1,548	1,548	1,548	4,408	4,408	4,408	4,408
R-squared	0.1413	0.1452	0.0796	0.1111	0.1640	0.1504	0.0712	0.0956

Table 4. Addressing Endogeneity Concerns of Self-Selected Post

Ruling Out Pretreatment Trends

Another potential concern in the DID model is whether there is a heterogeneity in the pretreatment trends between control and treatment groups. If there is a significant heterogeneity in the pretreatment trends, it suggests that the pretreatments may disproportionately affect treated units, as opposed to control units, and the "parallel path" assumption is less likely to be satisfied. In our context, the concern of pretreatment trends arises because unobserved socioeconomic factors in each local region may cause heterogeneity in the pretreatment trends, and more importantly, the pretreatment trends could affect medical institutions' decisions to post to users in online health platform. We use relative time model, which is developed by Greenwood and Agarwal (Greenwood and Agarwal 2015), to address this concern and results in Table 5.

	NCD	NDL	NDE	NDV
PostTreatment*TreatmentGroup(t+2)	-0.02 (0.068)	0.01 (0.053)	0.05 (0.028)	0.01 (0.016)

PostTreatment*TreatmentGroup(t+1)	0.042 (0.061)	0.099** (0.049)	0.083*** (0.03)	0.019 (0.016)
PostTreatment*TreatmentGroup(t-1)	0.271*** (0.062)	0.187*** (0.05)	0.082*** (0.028)	0.01 (0.017)
PostTreatment*TreatmentGroup(t-2)	0.265*** (0.072)	0.224*** (0.059)	0.116*** (0.032)	0.012 (0.018)
PostTreatment*TreatmentGroup(t-3)	0.22*** (0.076)	0.168*** (0.062)	0.082** (0.034)	0.053** (0.023)
PostTreatment*TreatmentGroup(t-4)	0.225*** (0.083)	0.13** (0.065)	0.065* (0.036)	0.014 (0.022)
Monthly dummies	Yes	Yes	Yes	Yes

Table 5. Results of the Relative Time Model

How Returns on MGC Vary over Time

In this section, we examine the moderating effect of medical institutions' age. In other words, we expect a variation in the returns on MGC due to the heterogeneity of medical institutions establishment time. We estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 PostTreatment_{it} + \beta_2(PostTreatment_{it} \times TreatmentGroup_i) + \beta_3(PostTreatment_{it} \times TreatmentGroup_i \times Age_i) + \beta_4 Controls + \alpha_i + \varepsilon_{it} \quad (2)$$

Where Age_i is the establishment time of medical institution i. In the regressions on moderating factors, we have the same controls as in regression Equation (1). The results are presented in Table 6. We find that the coefficient on the tripe interaction term is significantly positive, which suggests that post to users is more beneficial for the medical institutions with early establishment time than institutions with short establishment time. And the establishment time of medical institutions positively moderates the relationship between MGC and the number of customer diary and the number of diary with length. For the number of customer diary with emotion and the number of customer diary with video, however, the establishment time has no significant moderating effect.

	(1)NCD	(2)NDL	(3)NDE	(4)NDV
PostTreatment ×PopularSci	0.2929*** (0.0478)	0.1808*** (0.0358)	0.0295 (0.0213)	0.0157 (0.0122)
PostTreatment	0.00002*** (8.54e-06)	0.00002*** (6.41e-06)	5.21e-06 (3.81e-06)	1.13e-06 (2.19e-06)
Control variables	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes
Constant	1.6297*** (0.0695)	0.8269*** (0.0522)	0.4036*** (0.0310)	0.0489*** (0.0178)
R-squared	0.1502	0.1375	0.0614	0.1011

Table 6. Moderator effects of establishment time of medical institution

How Returns on MGC Vary over Geography

In this section, we investigate the role of medical institutions' city. We consider medical institution location because may be important to the relationship we are studying. Specifically, we divide the location of the medical institutions into two groups, namely, cities with high BaiduIndex and other cities, and then use $City_i$ as the measure for the group. We estimate the following regression equations:

$$Y_{it} = \beta_0 + \beta_1 PostTreatment_{it} + \beta_2 (PostTreatment_{it} \times TreatmentGroup_i) + \beta_3 (PostTreatment_{it} \times TreatmentGroup_i \times City_i) + \beta_4 Controls + \alpha_i + \varepsilon_{it} \quad (3)$$

Where $City_i$ is a binary variable indicating whether the medical institution i is located in cities with more online search behavior. If medical institution i is located in the city with more online search behavior, $City_i$ equal to 1, otherwise 0. In these regressions, we have the same controls as in Equation (3). The estimation results are presented in Table 7. Once again, the coefficient on the triple interaction term is significantly positive, which means that the location of medical institutions positively moderates the relationship between MGC and the number of diary, the number of diary with length, and the number of diary with emotion.

	(1)NCD	(2)NDL	(3)NDE	(4)NDV
PostTreatment×PopularSci	0.2715*** (0.0688)	0.2916*** (0.0515)	0.0686** (0.0306)	0.0265 (0.0176)
PostTreatment	0.3047*** (0.0449)	0.1741*** (0.0336)	0.0274 (0.0199)	0.0130 (0.0115)
Control variables	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes
Constant	1.6242*** (0.0687)	0.8159*** (0.0514)	0.3986*** (0.0305)	0.0476*** (0.0176)
R-squared	0.1479	0.1375	0.0589	0.0938

Table 7. Moderator effects of geography of medical institution

Mechanisms

Our main results and robustness tests consistently indicate the causal effects of MGC on UGC. Existing literature found that one of the ways firms encourage users to contribute knowledge in online communities is knowledge investment (Huang et al. 2018). Knowledge investment by firms in online communities helps build trust between firms and users(Jarvenpaa and Leidner 1998; Porter and Donthu 2008). Trust is a prerequisite for member interaction in online communities (Ridings et al. 2002). According to social norms theory, the norms emphasize a moral obligation toward others, arguing that actions taken by one party in an exchange relationship often result in reciprocate action by another party (Jarvenpaa and Leidner 1998).

In online health communities, medical institutions share valuable knowledge for users, such as sharing popular science knowledge rather than marketing knowledge, which shows that the firms truly care about the well-being of users beyond its own profit-seeking motivation. The firms' benevolent behavior creates a sense of moral obligation for users, which allows users to take reciprocal behaviors to restore equal relationship with firms (De Wulf et al. 2001). Therefore, the firm's knowledge investment encourages users to contribute content by establishing a trust relationship with users in online communities.

In the hypothesis development, we propose that MGC affects UGC because knowledge investment of medical institutions contributes to the users' knowledge contribution. For a comprehensive understanding of these effects, this study explores the moderating role of the importance of knowledge investment in medical institutions on the relationship between MGC and UGC.

This study uses the amount of content generated by medical institutions to characterize the importance of knowledge investment in medical institutions in online health communities. We change our Equation (1) by adding one interaction, $PostTreatment_{it} \times TreatmentGroup_i \times Postcnt_{it}$, where $Postcnt_{it}$ is the number of content by medical institution i at month t. The results reported in Table 8. The coefficient of the triple interaction term is significantly positive when the dependent variables are NCD_{it} and NDL_{it}

(Table 8, Model 1 and Model 2), indicating that medical institutions with a large number of posts attach great importance to knowledge investment, which has a large impact on the amount and length of UGC.

	(1) NCD	(2)NDL	(3)NDE	(4)NDV
PostTreatment×Treatment-Group×Postcnt	0.0071*** (0.0026)	0.0051* (0.0027)	0.0005 (0.0009)	0.0010 (0.0007)
PostTreatment×TreatmentGroup	0.3473*** (0.0645)	0.2188*** (0.0508)	0.0543** (0.0241)	0.0219* (0.0132)
TreatmentGroup	0.2665*** (0.0987)	0.1948*** (0.0621)	0.0631** (0.0270)	0.0163 (0.0110)
Control variables	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes
Constant	1.3124*** (0.1030)	0.6163*** (0.0671)	0.3349*** (0.0427)	0.0361** (0.0160)
R-squared	0.1544	0.1489	0.0668	0.1016

Table 8. DID Estimations on Medical Institutes with Different Content Volume

Moreover, we conduct subsample analyses to further understand how knowledge investment in medical institutions affects UGC. We first rank the medical institutions based on the number of content they generated in our study period. We treat medical institutions in the top 50th percentile as those who are interested in knowledge investment. There is a total of 242 medical institutions, and, on average, they generated 68.198 piece of content. Moreover, we consider medical institutions in the bottom 50th percentile as those who are not concerned about the knowledge investment. There is also a total of 242 medical institutions, and, on average, they produced 6.25 pieces of content. This study divides the dataset into two data subsets according to the top 50th and bottom 50th, and Table 9 presents the results of the subsample analyses. Panel (a) shows the results for the medical institutions in the top 50th percentile regarding the number of content generated in our study period, and panel (b) indicates the results for the medical institutions in the bottom 50th percentile. The results for the medical institutions in the top 50th percentile are consistent with our main results. Our results show that the medical institutions in the bottom 50th percentile do not significantly affect UGC when dependent variables are NDE_{it} and NDV_{it}. When the dependent variables are NCD_{it} and NDL_{it}, the medical institutions in the bottom 50th percentile have a much smaller impact on UGC than the medical institutions in the top 50th percentile. The impact of content generated by medical institutions in the top 50th percentile on the number of UGC is 19.12% ((0.4506 - 0.2584) * 100%) greater than that of medical institutions in the bottom 50th percentile. And the impact of content generated by medical institutions in the top 50th percentile on the number of UGC with long text is 16.75% ((0.2954 - 0.1279) * 100%) greater than that of medical institutions in the bottom 50th percentile. These results further validate our hypotheses that medical institutions that value knowledge investment is more able to stimulate UGC, comparable to institutions that do not value knowledge investment.

	Panel A: Medical Institutions in top 50th percentile				Panel B: Medical Institutions in bottom 50th percentile			
	(1)NCD	(2)NDL	(3)NDE	(4)NDV	(5)NCD	(6)NDL	(7)NDE	(8)NDV
PostTreatment×TreatmentGroup	0.4506*** (0.0860)	0.2954*** (0.0762)	0.1080*** (0.0392)	0.0525*** (0.0184)	0.2584*** (0.0881)	0.1279* (0.0682)	0.0107 (0.0335)	-0.0083 (0.0186)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Monthly dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Constant	1.6365*** (0.1420)	0.8307*** (0.0894)	0.4053*** (0.0657)	0.0672** (0.0275)	1.5630*** (0.1363)	0.7658*** (0.0893)	0.4751*** (0.0758)	0.0611** (0.0262)
Observations	3,499	3,499	3,499	3,499	3,305	3,305	3,305	3,305
R-squared	0.1483	0.1400	0.0509	0.1142	0.1547	0.1309	0.0630	0.1289

Table 9. Subsample Analyses

Due to differences in the degree of importance attached to knowledge investment by medical institutions in online health communities, medical institutions have different degrees of effort in knowledge investment. The difference in medical institutions' efforts to invest in knowledge affects UGC to varying degrees. We treat the length of posts issued by medical institutions as medical institutions' efforts in knowledge investment. We count the length of each month's posts by medical institutions during the study period. We change our Equation (1) by adding a tripe interaction term, $PostTreatment_{it} \times TreatmentGroup_i \times PostLen_{it}$, where $PostLen_{it}$ refer to the number of words posted by medical institutions i at month t. The results show that the length of posts has a significant positive moderate effect. Compared with low-effort medical institutions, the higher institutions' efforts to invest in knowledge, the more UGC they can obtain.

In addition, this study suggests that users are affected by reciprocity norms and will generate more quantity and richer content to return to medical institutions, because medical institutions care about the well-being of users beyond their own profit-seeking motives. To verify this mechanism, this study uses the number of popular science posts issued by medical institutions to characterize the benevolent behavior of medical institutions. We first conduct post tagging training for 5 people in the field of information systems. Then, taggers tagged 8,000 posts. There are a total of 60,887 posts in our study period, and we use Naive Bayes algorithm to classify the remaining 52,887 posts. Specifically, we establish a special vocabulary database for medical plastic surgery, and use jieba to segment the MGC and remove stop words. We divide the training set and the validation set into 30% and 70%, and obtain the Naive Bayes classifier with an accuracy of 88.75%. Finally, we calculate the number of popular science posts issued by medical institutions each month, $PopularSci_{it}$.

We change our Equation (1) by adding one interaction, $PostTreatment_{it} \times PopularSci_{it}$, to explore how the number of popular science posts published by medical institutions affects UGC. The results show that the popular science posts issued by medical institutions really benefits the quantity and linguistics features of UGC. Medical institutions that publish a large number of popular science posts are more concerned about users, so users are willing to generate more content for the purpose of returning medical institutions.

Discussion and Conclusions

In this study, we investigate the impact of firms' knowledge investment, as measured by marketer generated content, on the user generated content measure using the large online health platform. Our study fills an important gap in the literature by providing a deep understanding of the MGC on the quantity and linguistics features of UGC. We address the endogeneity concerns posed by self-selected posting by adopting multiple causal identification strategies and establishing a robust quantitative relationship between MGC and UGC measure.

Managerial Implications

Understanding the effects of firm generated content on user generated content using a social media feature in online health platforms is a new area of research. Our findings reveal that firms can nurture their customers' knowledge contributions by seeding the knowledge with their own marketers' contributions, a marketing strategy can be implemented at a relatively low cost. Our study suggests mechanism behind the effectiveness of this marketing strategy. Knowledge seeding by firms increases both customers' propensity to make knowledge contribution through enhancing the customers' collective body of knowledge. It would be useful to extend our work by studying how marketer generated content help improve the human capital of customers to the firm.

Second, this paper also contributes to the literature on firm-generated content, user-generated content, and the design of online health content systems. While past research has primarily focused on the consequences of user-generated content, our study provides a pioneering effort in understanding how an important system design feature—firm-generated content—affects volumes and linguistics features of UGC, based on prospect theory. Given the recent trend of online platforms toward promoting user content generation, it is crucial that we improve our understanding of the antecedent.

Third, our findings have direct implications for the firms and digital platforms. We observe that, the launch of the social feature benefits firms. However, the benefit is not observed in a consistent manner across all firms. Only the firms that choose to use the post feature observe increases in user generated content. On the other hand, the firms that are unaware of the post feature launch on digital platforms, or are aware but choose not to use the post feature, tend to remain at a disadvantage. Certainly, ignorance about newly launched features to engage with consumers on online community is not bliss for firms. Firms must keep an eye on the dynamic and evolving features offered by online platforms to effectively engage with their consumers.

Future Research Directions

There are several possible extensions to our research. First, we do not measure the effect of specific types of medical institutions on user generated content. Small, private medical institutions may function under different operating conditions and financial constraints. They may lack awareness about online health communities and may have limited resources to engage with consumers through post on digital platforms. On the other hand, large-scale chain, non-private medical institutions have the resources and financial support to invest in knowledge seeding on digital platforms. In the future, we would like to separately measure the impact of big and small of institutions post on user generated content, and propose customized strategies tailored to the specific type of institutions. Second, it would be interesting to conduct more text analyses on marketer generated content and user generated content. In this study, we examine the effect firms' knowledge seeding on user generated content with length, emotion and video. Additional analyses based on the content of marketers' posts and users' diaries can be done in the future. Finally, the impact of firms' knowledge seeding is significantly positive overall, but for a single observation, the effect might be insignificant because a particular marketer may write an ineffective post. A future research direction is to examine which types of marketer generated content are more likely to attract consumers and enhance user generated content.

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