Wooje Cho · Ming Fan
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Han Zhang (Eds.)

LNBIP 328

Digital Transformation: Challenges and Opportunities

16th Workshop on e-Business, WeB 2017
Seoul, South Korea, December 10, 2017
Revised Selected Papers

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Preface

The Workshop on e-Business (WeB) is a premier annual conference on e-business and e-commerce. The purpose of WeB is to provide an open forum for e-Business researchers and practitioners worldwide, to share topical research findings, explore novel ideas, discuss success stories and lessons learned, map out major challenges, and collectively chart future directions for e-Business. Since 2000, WeB has attracted valuable and emerging research and followed closely the developments in the technical and managerial aspects of e-business. The 16th Annual Workshop on e-Business (WeB 2017) was held in Seoul, South Korea, on December 10, 2017.

The theme of WeB 2017 was "Digital Transformation: Challenges and Opportunities." Digitalization, consumerization, global platforms, and transformative innovations are causing industry convergence at a record pace. Information technologies are constantly changing business models and firms cannot but lag behind competitors in industry without understanding new information technology. That is to say, information technology can give firms great opportunities and it can give some firms critical challenges. New information technologies such as business analytics and social media networks are constructed properly and effectively engage customers. This enabled both firms and consumers to take advantage of the global supply of goods and services over the Internet and logistics.

WeB 2017 provided an opportunity for scholars and practitioners to exchange ideas and share findings on the themes. Original research articles with a broad coverage of behavioral issues on consumers, citizens, businesses, industries, and governments, ranging from technical to strategic issues were presented at the workshop.

Among 43 papers presented at WeB 2017, 11 paper were selected to be published in this volume of LNBIP. We would like to thank all the reviewers for their time and effort and for completing their review assignments on time despite tight deadlines. Many thanks to the authors for their contributions.

July 2018

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Contents

Attracting Versus Sustaining Attention in the Information Economy 1
Yimiao Zhang and Kim Huat Goh

Exploration of the Misalignment Between Business and IT Strategic Objectives in Public-Sector Organisations: An Empirical Study in Saudi Arabia. 15
Abulaziz AlGhazi, Mengxiang Li, Tingru Cui, Samuel Fosso, and Jun Shen

Influences of Place Attachment and Social Media Affordances on Online Brand Community Continuance (Research-in-Progress) 29
Kai Wang, Jeffrey C. F. Tai, and Hsin-Lu Chang

Factors Influencing Employees' Attitude Towards Personal Information Privacy. 38
Shin-Yuan Hung, Kuo-Jung Shen, and Tsan-Ching Kang

How Does the Review Tag Function Benefit Highly-Rated Popular Products in Online Markets?. 47
Zhuolan Bao, Wenwen Li, Pengzhen Yin, and Michael Chau

Antecedents and Consequences of App Update: An Integrated Research Framework 64
Hengqi Tian and Jing Zhao

Is There a Free Lunch? Examining the Value of Free Content on Equity Review Platforms 79
Tianyou Hu and Arvind Tripathi

Why Do You Need to Buy Virtual Items?: Investigating Factors Influencing Intention to Purchase in Mobile Games 87
Moonkyoung Jang, Rumi Lee, and Byungjoon Yoo

A Theory of Information Biases on Healthcare Platforms. 94
Zhenhua Wu, Zhijie Lin, and Yong Tan

The Power of Facebook and Instagram Fans: An Exploration of Fan Comments and Their Effect on Social Media Content Strategy 109
Hamidreza Shahbaznezhad, Rebecca Dolan, and Arvind K. Tripathi

Trial and Pricing Strategies of Software Market with Competition and Network Effects 118
Zhenhua Wu, Zhijie Lin, and Yong Tan

Author Index 131

Attracting Versus Sustaining Attention in the Information Economy

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Abstract. Attention is a scarce resource possessed by a person. In the information age, we observe the rapid increase of information available and the decrease of individual's attention. This calls for efficient attention allocation amidst information overload. Prior literature suggests attention allocation is a two-stage process – attracting attention and sustaining attention. In this study, we refer to attention theory from psychology literature to explore what attract users' attention and why users stay on with particular social media content. We use YouTube as the empirical setting to differentiate attracting attention from sustaining attention and examine factors that influence attracting and sustaining attention. The results of this study show that factors that attract attention are different from the factors that will sustain attention in the information age.

Keywords: Attention economy · Attention theory · Econometrics
Social media · YouTube

1 Introduction

The exponential growth of the information brought about immense competition within the attention economy. Attention is defined as "focused mental engagement on a particular item of information" [1]. In the attention economy theory, attention is a resource possessed by a person and this resource is constantly facing competition and scarcity [2–4]. This argument is premised on two tenets. First, attention is a resource. Specifically, information consumes the attention of its recipients [5] to the extent whereby attention is touted by some as the new currency in the information age [1]. Consumers are spoilt for choices in information content and content which are able to attract and maintain the attention of individuals will be able to use this window of opportunity to shape their beliefs. Naturally, the ability to shape beliefs on issues ranging from what brand of soap to buy to which politician to vote for translates into value which the content provider or carrier can monetize [3]. Second, attention is scarce. The attention possessed by any person is limited [1, 2] and it is impossible for people to "pay attention" to every item, or every piece of information in the world. As a result, information competes for individual's attention [2]. For example, when you load your Facebook page, you are not able to check out every post, every advertisement, or every notice which are competing for your attention.

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With the features of the attention economy in mind, there are two notable phenomena. First, people's attention span is short and is decreasing. Brown [6] argued that exposure to the digital world diminishes our attention span in work, entertainment and learning. Liu [7] surveyed reading behavior in the digital environment and found that online users spent less time on in-depth, concentrated reading compared to ten years ago. Second, the amount of available information is rapidly increasing. In the information age, people are able to explore vast amount of information online. The last decade witnesses the rise of social media, from the likes of knowledge-driven Wikipedia to the likes of relationship-driven Facebook. Incredible amount of information is generated in social media every second. For example, 7599 Tweets are send and 779 Instagram photos are uploaded in one second [8].

Juxtaposing the tenets of the attention economy with the phenomena of declining attention within a climate of growing information, begs the following question. What attracts and more importantly sustains individual's attention in the information economy? Given that attention is scarce and declining, attracting and sustaining attention will become increasingly more difficult with more avenues of competition from different information sources. In this study, we take exploratory steps to examine what are the factors that attract and sustain attention of individuals in this information economy. We situate our study in an empirical context and hope to unpack the psychological underpinnings which lead to greater focus and attention. We use YouTube as the empirical setting to distinguish attracting and sustaining attention on social media. We apply attention theory from psychology literature to explore what attract users' attention and why users stay on with particular social media content. The results of this study show that factors that attract attention to informational content are different from the factors that will sustain the attention. For example, we see positive relationship between color contrast and attention attraction. To sustain the attracted attention on the other hand is a result of consistency in content.

2 Literature Review on Attention in Social Media

Prior literature has shown that individuals pay attention to a piece of online information is a two-stage process [7, 9, 10]. In the first stage, a user is attracted by a piece of information because of some reasons, for instance, the highlighted words, the prominent position, or the attractive picture. Once a user is attracted, in the second stage, he or she spend some time with this piece of information by reading the content. Therefore, online content creators are facing the challenges of (1) attracting user attention and (2) sustaining user attention.

Some research efforts have been made to examine the factors that attract users' attention [10–13]. In many social media platforms, for instance Facebook, Twitter, and Instagram, whereby there is no direct measurement of view count, indirect proxies such as number of likes, number of comments, or number of sharing are used to reflect the attraction of users' attention. These proxies are used based on the assumption that the social media content has attracted a user's attention earlier which ensue these user activities. Chatzopoulou et al. [14] showed that number of comments, number of like, and number of favorites are highly correlated to social media content view count.

In other online platforms such as YouTube, where we can observe the number of views of each video, we know how many individuals who have clicked on the content and spent some time with it – hence a more direct measurement of user attention attraction.

Prior studies have investigated various factors that impact YouTube video view count. Zhou et al. [15] found that YouTube recommendation system is an important factor that drives video view count. Recommendation systems generally provide content related to the referent video a user is watching and this supplements the view instances from direct searching of a video [9, 15]. As in any social media platform, social factors on YouTube can play an important role to video popularity and view instances. In particular, social networks sizes of the YouTube video and YouTube users contribute positively to video view count. View count of a focal video is highly correlated with view count of videos in the same playlist [16]. Further, YouTube user friends' network size has significant impact on the growth of view count over time [17]. Extant literature also point out the effect of geographic locality on video view count. About 50% of videos receive more than 70% of their total view count from a single country, however, social sharing widens a video's geographic audience [18]. To the best of our knowledge, prior studies only examined what attract user attention rather than sustaining user attention in the social media context. In this paper, we will look at both processes that influence the attraction as well as the retention of attention.

3 Theory and Hypotheses Development

In this study, we refer to psychology theories to guide our hypotheses.

3.1 Visual Attention – The Bottom-Up and Top-Down Frame

Online platforms such as YouTube tend to adopt visual stimuli (such as placement of links, color, font size etc.) as the predominant cues to attract attention. To this end, we look at some factors that influence visual attention for online videos. Visual attention is also known as selective attention in vision. The stimuli that are to be processed are the characteristics of images received visually. Literature has point out that people have limited attention because of cognitive bottlenecks when processing incoming stimuli [19–23]. Similarly, individuals can only pay attention to a limited number of visual objects. In the visual attention research, a bottom-up and top-down framework provides an explanation for the mechanism which helps determined which visual cues are being passed through the bottleneck for processing [24–31]. Briefly, the bottom-up mechanism is a stimuli-driven mechanism which posits that visual attention is attracted by the saliency of the stimulus. The top-down mechanism is a knowledge driven selection mechanism whereby the individual intentionally locate the visual target based on some subjective, pre-determined criteria.

In the bottom-up selection, the saliency of a stimulus drives visual attention. When the characteristics of a stimulus stands out from the environment on one dimension or combined dimensions [30, 32], it attracts visual attention. The features of visual stimuli that gains visual attention can be on various dimensions, such as color, orientation, brightness, size, location, and intensity [27, 30]. Experiments have shown that salient color comparing to surroundings helps to facilitate visual selection [30, 33, 34]. Other studies have also shown that luminance contrast is a primary feature that makes the stimulus salient and contributes to attracting visual attention [35]. In particular, high contrast luminance of an image triggers visual attention. Similarly, we expect that high color contrast is a salient stimulus that attracts visual attention. Therefore, we hypothesize that an image with high color contrast on a social media page is more likely to attract users' visual attention.

Hypothesis 1 (H1): An image with high color contrast on a social media platform is more likely to attract users' visual attention to click on it.

When an individual has a predetermined selection criterion or a clear intention of what he or she is looking for, the visual attention selection follows a top-down mechanism. In the top-down selection, subjective intention is the key driver of visual attention allocation. The top-down selection is an important mechanism in the social media context. Social media platforms allow users to "follow" accounts they are interested in. The ability to search for various themes using keywords will allow the individual to identify the source of such content and allows these sources to be "followed". Given that there is more information on social media than any user could pay attention to, the act of "following" creates the necessary filters to allow only information is going to focus more through the processing bottleneck and leads to users to pay visual attention to the content posted by the accounts they are following. Therefore, the more followers an account has, the more visual attention it will attract.

Hypothesis 2 (H2): On social media platforms, the number of followers is positively related to the visual attention it receives in the form of click views.

3.2 Sustained Attention: Stimulation Level

Capturing the attention of individuals online is the first integral part of this study; examining what helps maintain this attention is probably the more important issue in social media platforms. To look at what influences continued interest and attention, we will have to examine how individuals perceive environmental stimuli over time.

We are constantly bombarded by different types of environmental stimuli every day which vary in terms of their level of excitement. Research has shown that people have a need for an appropriate stimulation level which is called optimal stimulation level (OSL) [36–38] to maintain interest and attention. Optimal stimulation level is an individual characteristic that varies from person to person. If the environmental stimulus is lower (higher) than an individual's optimal stimulation level, she will feel bored (uncomfortable) and want to increase (reduce) the stimulation level by changing the environment stimulus.

In the social media context, we argue that the temporal stimulation level influences users' sustained attention. When a social media user views a particular content, sustained viewing is contingent upon the pace of which the content is being delivered. Based on the theory of optimal stimulation level, maintaining stimulation consistently within a reasonable range is essential to prevent the user from being under or over-stimulated and hence discontinue viewing. Further, inconsistency and punctuation in the simulation levels is likely to cause a drop in the simulation level. For example, a professor is giving an interesting lecture but interrupted by some technical fault. In this case, the consistent informational content pace is interrupted and students' attention are likely to be momentarily lost. Therefore, we expect that consistency in informational content pace facilitates sustained attention.

Hypothesis 3 (H3): On social media platforms, consistency in informational content's pace is positively related to sustained attention.

In addition, we also expect consistency (coherence) in content topic variety is important to sustaining attention. Although prior research in consumer behavior has shown that variety in general increases stimulation level [37–39], it is important to note that the relationship between variety and heightening interest is not without bounds. For example, an individual who loves to ski might wish to ski in different parts of a ski mountain (variety in the view, difficulty and gradient), he or she however might not like the idea of say snowboarding instead of skiing. Similarly, to sustain user's attention, content topic variety maybe helpful, it has to be coherent. Coherent topic helps to maintain the content stimulation level at a certain level. Besides, if the content topic varies without coherence, the content falls to low quality and user's attention could be distracted by other stimuli. Therefore, we expect coherence across information content is positively related to sustained attention.

Hypothesis 4 (H4): On social media, coherence in content topic variety is positively related to sustained attention.

4 Methodology

4.1 The YouTube Context

We use YouTube as the research context in this study. On YouTube, each registered user has a YouTube account (also known as channel) and can subscribe to one another. The act of subscription is just similar "following" on Twitter. To view videos, users can either browse the videos on home page or actively search for videos. For registered users, popular videos uploaded by accounts they have subscribed to are also presented on their home page when they login. The predominant information content provide on YouTube is video and limited information (such as title, content source, and publish time) is presented with the link prior to watching the video. Users need to click the link in order to view the full content and like most information good, consumption of the good requires the investment of time and attention.

4.2 Data Collection Approach

We collect the data from YouTube between 22 July 2016 and 22 September 2016. We create Python scripts with YouTube data API to extract all the accounts from the entertainment and sports categories. We choose these categories because they contain a wide variety of videos with great heterogeneity in terms of viewership lengths and popularity. We tracked all the videos published in these categories from all the accounts from 22 July 2016 till 19 Aug 2016 (4 weeks duration) and for each video, we continuously collect all relevant data on a daily basis for at least 1 month. Daily collection is required as some data, such as number of views, number of likes, and number of comments is dynamic over time. Data from a total of 13784 videos is collected.

In order to investigate how the video conversation pace and video topics affect sustained attention, we extract the video captions generated by YouTube for the uploaded videos. Account owners have an option enable the caption function. In addition, we also filter out videos with only one-sentence caption, as they commonly include only the video title and not the contents of the video. Given that the captions are automatically generated by YouTube system, we often observe that poorly-shot videos with inferior sound quality are often without captions due to difficulty experienced in the captioning process. The data set has 370 videos with captions. Each video on YouTube belongs to video type, while an account is assigned to a channel category (e.g. sports) by YouTube only when the account have uploaded a certain number of videos, most of which belongs to a same video type (e.g. sports). In total, we get 986 channels from the two categories (sports and entertainment). That's why the final sample size is not very large. This data represents a sample of relatively well-designed, properly formatted, quality social media content, and this makes it an ideal sample for us to examine the factors that impact attention attraction and retention. For the remaining videos that do not have captions, we used them as the comparative data points for Heckman selection bias correction (details later). We are currently in the process of randomly selecting additional videos that do not have captions and subject them to YouTube's captioning process to test the robustness of our initial results presented later.

4.3 Text Mining

To obtain the proxy measures for coherence in video topic, we conduct topic modeling that applies statistical methods to discover the topics that appear using the video captions. We adopt the Latent Dirichlet Allocation (LDA) topic model [40], which is commonly used in prior studies [41–43]. In running the algorithm, we define the total number of topics (k) that will be generated and tried various iterations of k (k = 10, 20, 30, 40, 50, 60, 70, 80, 90, 100). Each discovered topic is represented by the most frequent words and topic modeling generates loadings of each document for each topic. The loading measures the likelihood of the content belonging to the corresponding topic. For every video caption, it is scored against all topics, k, and we use the loadings to calculate the degree of video topic coherence (operationalization details in the next section).

In this study, we performed sentiment analysis on video title and video description. Sentiment analysis is a text mining technique that identifies the sentiment of text basing on the polarity (positive, neutral, or negative) of words occur in the text. We use the Stanford coreNLP R package to conduct the sentiment analysis [44]. The Stanford coreNLP package first splits the texts into single sentences and sentiment analysis is conducted on each sentence. As a result, each sentence gets a sentiment score (from 0 to 4) and sentiment score of the sentences are aggregated and averaged. The corresponding representation of 0 is very negative, 1 is negative, 2 is neutral, 3 is positive and 4 is very positive.

4.4 Variables and Measurement

This study has two dependent variables, *visual attention* and *sustained attention*. *Visual attention* is the attracted attention of a video and we use daily view count to proxy the visual attention. View count is the number of users who have clicked on to a link to play the video regardless of the duration they watch it. *Sustained attention* is the amount of attention a user pays to a video. Conceptually, the longer one spends watching a video, the longer the attention is being attributed. We use the ratio of daily average video view duration to the total video duration to measure sustained attention. We use the ratio rather than the absolute video view duration as videos vary in duration, and taking absolute duration will result in dependent variable that has different upper limits for this metric. The higher the ratio, the higher proportion a video is watched i.e. the longer attention is sustained with this video.

There are four key independent variables of interest in this study. *Color contrast* is measured by the average gradient of each pixel on red, green, blue (RGB) values in a video thumbnail. We choose to measure the contrast of the video thumbnail as this is the only image users will see before clicking onto the video. We calculate the gradients on R, G and B of each pixel in thumbnails and then get the average gradients of all pixels on R, G and B respectively. A higher gradient represent an image with more vibrate and striking variation in color tones. Finally, we take average of the three average values to measure the color contrast. *Number of followers* is measured by the total number of subscribers of YouTube channel. Each YouTube channel represents an account which is permitted to post videos and subscribe to.

To proxy the pace of information content, we measure *video conversation pace*. Here, we identify all the periods of silence whereby there is no conversation in the video. We measure the time duration of each block of silence and compute the variance of these durations throughout the video. A video that has a consistent (inconsistent) video conversation pace has a low (high) variance. Given that the videos in this sample have substantial captions, we believe that these videos are conversational in nature and do not contain solely moving imagines. As a result, the conversational content represents an important part of the stimuli that is required to maintain the user's attention. The last independent variable is *video topic coherence*. We adopt the economic concept of Herfindahl-Hirschman Index (*HHI*) which measures the industry concentration to calculate video topic concentration and coherence [45]. A high (low) *HHI* represents high (low) concentration. We adapt the *HHI* for video topic coherence, C_i:

$$C_i = \sum_{j=1}^{k} \left(\frac{L_{ij}}{\sum_{j=1}^{k} L_{ij}}\right)^2 \tag{1}$$

Where L_{ij} is the loading of video i on topic j, (i.e. the degree of which the contents of the video i fall into topic j). k is the total number of topics for all the videos. Given that each topic constitute a collection of commonly occurred words which are lexically similar, a video which spread across multiple topics (low C_i) is likely to be less coherent than another which is concentrated into fewer topics (high C_i). In our analysis, we use 60 as the number of topics ($k = 60$). Given that the dataset contains many videos on various topics, to cover these topics, a large k is more reasonable than a small k [46]. We try various iterations of k from 10 to 100 (in intervals of 10), and found that $k >= 60$ is more meaningful than $k <= 50$ as the classification results appears to be more stable beyond 60. In addition, empirical estimation of our regression models revealed similar results for $k = 60, 70, 80, 90$ and 100.

Control variables in this study include *video age*, *video duration*, sentiment of video title (*sentiment_title*), *number of meaningful words*[1] of video title (*no_word_title*), sentiment of video description (*sentiment_des*), number of meaningful words of video description (*no_word_des*), daily sharing count (*daily_sharing*), video cumulative view count (*video_view_cum*), video tag count (*tag*), *video category*[2], daily video like count (*daily_like*), daily video dislike count (*daily_dislike*), daily video comment count (*daily_comment*), *channel age*, *channel location*[3], channel video count (*channel video*), and channel comment count (*channel comment*).

4.5 Analysis and Models

We propose the *visual attention* for a video, i, at time, t, days since data collection, is a function of the color contrast (*color*) of the video thumbnail (H1), the number of followers (*no_followers*) the channel (H2) has as well as other exogenous time invariant factors U_i and time variant control factors P_{it}. Specifically:

$$\begin{aligned} &Visual\ attention_{it} \\ &\quad = \beta_0 + \beta_1 Color_i + \beta_2 No\_followers_{it} + \beta_3 U_i + \beta_4 P_{it} + V_i + W_t + \Omega_i + \varepsilon_{it} \end{aligned} \tag{2}$$

Where β represent parameters of the model, ε represents stochasticity across video and time, V represents video level stochasticity, Ω_i represents the inverse mills ratio to control for self-selection biases in the presence of subtitles, and W represents time level stochasticity.

Additionally, we proposed that the sustained attention (*sust_attention*) of the video is a function of the conversation pace (*conv_pace*) (H3), topic coherence (*topic_cohe*) (H4) and other exogenous time invariant factors K_i and time variant control factors J_{it}.

[1] Meaningful words contain non-function words such as conjunctions, pronouns, and auxiliary verbs.

[2] Video category of our dataset includes film & animation, sports, travel & event, people & blogs, comedy, entertainment, howto & style, and education. Video category is based on the video content and is different from channel category.

[3] The channels of the dataset are from four countries, US, CA, GB, and CH.

Sust_attention is a portion of two variables and the value is between 0 and 1. In the regression, we multiply the value of *sust_attention* by 100, so the unit of the variable *sust_attention* becomes %.

$$Sust\_attention_{it} = \gamma_0 + \gamma_1 Conv\_pace_i + \gamma_2 Topic\_cohe_i + \gamma_3 K_i + \gamma_4 J_{it} + V_i + W_t + \Omega_i + \varepsilon_{it} \tag{3}$$

Where γ represent parameters of the model, ε represents stochasticity across video and time, V represents video level stochasticity, Ω_i represents the inverse mills ratio to control for self-selection biases in the presence of subtitles, and W represents time level stochasticity.

In both Eqs. (2) and (3) we included a time-related error term W to partial out any stochasticity due to temporal differences (e.g. time periods with more online traffic due to seasonal differences). Similarly, we also included a video-level error term V to control for any video-level idiosyncrasies which were not captured by our exogenous variables. Notably, we applied Heckman selection model on the 13,784 videos to correct for potential sample selection bias given that the presence of captions is elective, and estimate (2) and (3) using random effects model with white-adjusted standard errors to mitigate any heteroscedasticity issues.

5 Results and Discussion

5.1 Attention Attraction

For the testing of H1 and H2, we refer to the results of Model 1 in Table 1. We suppressed all the control variables for brevity and list them in the footnote below the table. In model 1, the link between thumbnail color contrast and visual attention is positive and significant (coeff: 69.660; p-value < 0.05), which means, higher color contrast is more likely to attract users' attention, indicating support for Hypothesis 1. The results also show significantly positive relationship between number of followers and visual attention (coeff: 0.002; p-value < 0.001), indicating support for Hypothesis 2. The coefficient of number of followers may be numerically small, but it does not suggest the lack of physical significance because of the large number of followers relative to daily view count.

The estimates of Eq. (2) suggest the existence of both bottom-up and top-down visual attention selection processes in the social media platform. In the bottom-up process, image color contrast is an important stimulus to facilitate visual attention when many images are shown at the same time. The relationship between number of followers and user attention attraction suggests the importance of personal interests in determining selection. Overall, although attracting attention on social media may be interest or intention driven (top-down), the importance of bottom-up salient stimuli on users' visual attention selection process cannot be overlooked.

Table 1. Regression results for visual attention and sustained attention

Model 1	DV: Visual attention	Model 2	DV: Sustained attention
Variables	Coefficients (Std. Err.)	Variables	Coefficients (Std. Err.)
Intercept	3650.077 (17181.470)	Intercept	10.082 (41.140)
No_follower	0.002*** (.000)	Conv_pace	−0.197** (0.070)
Color contrast	69.660* (34.944)	Topic_cohe	24.532** (8.273)
Controls[a]	<suppressed for brevity>	Controls[b]	<suppressed for brevity>

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

[a]Control variables for H1 and H2 are video age, video duration, sentiment_title, no_word_title, daily_sharing, video_view_cum, tag, video category, channel age, channel location, channel video, and channel comment.

[b]Control variables for H3 and H4 are sentiment_title, no_word_title, sentiment_des, no_word_des, color contrast, video age, video duration, video_view_cum, tag, daily_like, daily_dislike, daily_comment, daily_sharing, video category, channel age, channel location, no_follower, channel video, and channel comment. Controls omitted for brevity in presentation.

5.2 Attention Sustaining

The estimates of Eq. (3) are used to test Hypothesis 3 and 4 (refer to Model 2 in Table 1). As hypothesized in H3, we find negative and significant relationship between video conversation pace value and sustained attention (coeff: −0.197; p-value < 0.01). When the variance in the conversation pace increases, we see a drop in the proportion of the video being viewed, supporting Hypothesis 3. The relationship between video topic coherence and sustained attention is positive and significant (coeff: 24.532; p-value < 0.01), suggesting users' attention are more likely to be sustained by a videos with more coherent topics throughout the clip. Hypothesis 4 is supported.

The estimates from Eq. (3) suggest that consistency in stimulation is important to sustained attention. Consistent video conversation pace and coherent video topic keeps the stimulation at a certain level and maintains the interest level of the viewer. When video conversation pace is not consistent, users will experience varied stimuli with periods of intense content followed by slow, monotonous content. Additionally, maintaining coherence across the video topics over time also helps maintain the stimuli at a certain optimal level. Although variety can increase the stimulation level, the coherences within the variety across different topics in a single video is essential. Further, we can infer from the results that users have their preference when they watch a video. If a user is attracted to a video because of the account or title information, the user may have a clear, desired video topic in mind. When the video deviates from the desired topic by introducing more topics than the user expects, the added irrelevant topics will make it hard for the user to sustain his or her attention. In sum, consistency in video conversation pace and coherence in video topic are significant factors to sustained attention.

6 Contribution to Literature and Practice

In this study, we use YouTube as the research context to distinguish attracting attention and sustaining attention on social media and take exploratory steps to examine what are the factors that attract and sustain attention of individuals in this information economy.

This study contributes to the existing conversation of attention theory in psychology particularly within the social media context. In deconstructing how social media users get attracted to information content visually, we showed that they follow a bottom-up and top-down process [24–31], such that color contrast of a video's thumbnail is an important stimulus which triggers the bottom-up process of attracting attention to the referent video thereby increasing the click through rate; and users also click through social media videos via a top-down process where their video selection is more directed as a result of having followed the video channel.

The current bottom-up and top-down mechanisms within the attention literature only explains what kind of stimuli can get through the information processing bottleneck, with limited discussion on what contributes to sustaining attention of the stimuli beyond the bottleneck. Our results suggested that consistency in stimulation level is critical to sustaining attention in the social media context. Further, we found consistency in video conversation pace and coherence of video topics over time are two factors to sustain users' attention. We believe that the results of this study are not just limited to video, but can be generalized to other text-based user generated contents or audio recordings on social media platforms.

This study also contributed to the practice. As discussed before, due to the limited attention possessed by people, there exist severe competitions among social media online content creators. The results of this study provide implications for online content creators by identifying factors that can attract users' attention and sustain users' attention, especially for YouTube video uploaders. Content creators can adjust their content creation strategies, for instance, choosing high color contrast images as thumbnails of their videos, encouraging users to subscribe to their accounts, and designing the content with consistent informational pace and coherence in topic selection, to attract and sustain more attention, and achieve success.

7 Limitation and Future Research

This study is not without limitations. Due to practical data collection reasons, we examine the phenomenon using individual video over time as the unit of analysis and not individual user viewing patterns. As a result, we are unable to measure individual's optimal stimulation level, and rely on the law of averages to approximate that if a user is attracted by a video (by viewing it), the initial or expected stimulation level should be close to his or her optimal stimulation level. One possible way to mitigate this limitation is to consider conducting experiments to track users' physiological response to videos with different conversation pace and videos with different topic coherence level.

The presence of advertisements in a video may affect the sustained attention as advertisements interrupt a video and provide irrelevant information. In this study, we didn't consider the effect of advertisements because the insertion of advertisements in a

YouTube video is not readily measured and can be dependent on various factors such as timing and browsing history of the individual. Nevertheless, assuming that the algorithmic process of inserting these advertisement are consistent within the time period of two months of which we collect the data, we should see limited impact on our results as they can be captured by the video level error term specified in our estimation model. Nevertheless, to completely mitigate this issue, future research can consider conducting experiments to test the effects of advertisements in a video on sustained attention, as it will be interesting to investigate the effects of position in a video and length of advertisements on sustained attention.

8 Conclusion

In this study, we took exploratory steps to examine the factors that attract and sustain attention of individuals in this information economy. We situated our study in an empirical context and hope to unpack the psychological underpinnings which lead to greater focus and attention. We used YouTube as the empirical setting to differentiate attracting attention from sustaining attention on social media and examined the different factors that influence attracting and sustaining attention. The results of this study showed that color contrast of a video thumbnail and number of followers for a social media content creator has are important factors to attract attention following a bottom-up and top-down search process respectively. Further, consistency in stimulation level and coherence in content topic matter were found to sustain the attracted attention.

References

1. Davenport, T.H., Beck, J.C.: The Attention Economy: Understanding the New Currency of Business. Harvard Business Press, Boston (2001). https://doi.org/10.1145/376625.376626
2. Falkinger, J.: Limited attention as a scarce resource in information-rich economies. Econ. J. **118**(532), 1596–1620 (2008). https://doi.org/10.1111/j.1468-0297.2008.02182.x
3. Goldhaber, M.H.: The attention economy and the net. First Monday **2**(4) (1997). https://doi.org/10.5210/fm.v2i4.519
4. Pedrycz, W., Chen, S.-M.: Social Networks: A Framework of Computational Intelligence, vol. 526. Springer, Cham (2013). https://doi.org/10.1007/978-3-319-02993-1
5. Simon, H.A.: Designing organizations for an information-rich world. In: Greenberger, M. (ed.) Computers, Communication, and the Public Interest, pp. 40–41. The Johns Hopkins Press, Baltimore (1971)
6. Brown, J.S.: Growing up: digital: how the web changes work, education, and the ways people learn. Change Mag. High. Learn. **32**(2), 11–20 (2000). https://doi.org/10.1080/00091380009601719
7. Liu, Z.: Reading behavior in the digital environment: changes in reading behavior over the past ten years. J. Documentation **61**(6), 700–712 (2005). https://doi.org/10.1108/00220410510632040
8. InternetLiveStats (2017). http://www.internetlivestats.com/one-second. Accessed 3 May 2017

9. Figueiredo, F., Benevenuto, F., Almeida, J.M.: The tube over time: characterizing popularity growth of youtube videos. In: Proceedings of the Fourth ACM International Conference on Web Search and Data Mining, pp. 745–754. ACM (2011) https://doi.org/10.1145/1935826.1935925
10. Szabo, G., Huberman, B.A.: Predicting the popularity of online content. Commun. ACM **53**(8), 80–88 (2010). https://doi.org/10.1145/1787234.1787254
11. Bakshy, E., Rosenn, I., Marlow, C., Adamic, L.: The role of social networks in information diffusion. In: Proceedings of the 21st International Conference on World Wide Web, pp. 519–528. ACM (2012). https://doi.org/10.1145/2187836.2187907
12. Cha, M., Haddadi, H., Benevenuto, F., Gummadi, P.K.: Measuring user influence in Twitter: the million follower fallacy. ICWSM **10**(10–17), 30 (2010)
13. De Vries, L., Gensler, S., Leeflang, P.S.: Popularity of brand posts on brand fan pages: an investigation of the effects of social media marketing. J. Interact. Mark. **26**(2), 83–91 (2012). https://doi.org/10.1016/j.intmar.2012.01.003
14. Chatzopoulou, G., Sheng, C., Faloutsos, M.: A first step towards understanding popularity in YouTube. In: INFOCOM IEEE Conference on Computer Communications Workshops, San Diego, CA, USA, pp. 1–6. IEEE (2010). https://doi.org/10.1109/infcomw.2010.5466701
15. Zhou, R., Khemmarat, S., Gao, L.: The impact of YouTube recommendation system on video views. In: Proceedings of the 10th ACM SIGCOMM Conference on Internet Measurement, pp. 404–410. ACM (2010). https://doi.org/10.1145/1879141.1879193
16. Cheng, X., Dale, C., Liu, J.: Statistics and social network of YouTube videos. In: 16th International Workshop on Quality of Service, IWQoS 2008, Enschede, Netherlands, pp. 229–238. IEEE (2008). https://doi.org/10.1109/iwqos.2008.32
17. Susarla, A., Oh, J.-H., Tan, Y.: Social networks and the diffusion of user-generated content: evidence from YouTube. Inf. Syst. Res. **23**(1), 23–41 (2012). https://doi.org/10.1287/isre.1100.0339
18. Brodersen, A., Scellato, S., Wattenhofer, M.: Youtube around the world: geographic popularity of videos. In: Proceedings of the 21st International Conference on World Wide Web, pp. 241–250. ACM (2012). https://doi.org/10.1145/2187836.2187870
19. Broadbent, D.: Perception and Communication (1958)
20. Deutsch, J.A., Deutsch, D.: Attention: some theoretical considerations. Psychol. Rev. **70**(1), 80 (1963). https://doi.org/10.1037/h0039515
21. Norman, D.A.: Toward a theory of memory and attention. Psychol. Rev. **75**(6), 522 (1968). https://doi.org/10.1037/h0026699
22. Treisman, A.M.: Contextual cues in selective listening. Q. J. Exp. Psychol. **12**(4), 242–248 (1960). https://doi.org/10.1080/17470216008416732
23. Treisman, A.M.: Selective attention in man. Br. Med. Bull. **20**(1), 12–16 (1964). https://doi.org/10.1093/oxfordjournals.bmb.a070274
24. Buschman, T.J., Miller, E.K.: Top-down versus bottom-up control of attention in the prefrontal and posterior parietal cortices. Science **315**(5820), 1860–1862 (2007). https://doi.org/10.1126/science.1138071
25. Connor, C.E., Egeth, H.E., Yantis, S.: Visual attention: bottom-up versus top-down. Curr. Biol. **14**(19), R850–R852 (2004). https://doi.org/10.1016/j.cub.2004.09.041
26. Desimone, R., Duncan, J.: Neural mechanisms of selective visual attention. Ann. Rev. Neurosci. **18**(1), 193–222 (1995). https://doi.org/10.1146/annurev.ne.18.030195.001205
27. Itti, L., Koch, C.: A saliency-based search mechanism for overt and covert shifts of visual attention. Vis. Res. **40**(10), 1489–1506 (2000). https://doi.org/10.1016/S0042-6989(99)00163-7

28. Sarter, M., Givens, B., Bruno, J.P.: The cognitive neuroscience of sustained attention: where top-down meets bottom-up. Brain Res. Rev. **35**(2), 146–160 (2001). https://doi.org/10.1016/S0165-0173(01)00044-3
29. Theeuwes, J.: Top–down and bottom–up control of visual selection. Acta Physiol. (Oxf) **135**(2), 77–99 (2010). https://doi.org/10.1016/j.actpsy.2010.02.006
30. Treisman, A.M., Gelade, G.: A feature-integration theory of attention. Cogn. Psychol. **12**(1), 97–136 (1980). https://doi.org/10.1016/0010-0285(80)90005-5
31. Itti, L., Koch, C.: Computational modelling of visual attention. Nat. Rev. Neurosci. **2**(3), 194–203 (2001). https://doi.org/10.1038/35058500
32. Itti, L., Koch, C.: Computational modelling of visual attention. Nat. Rev. Neurosci. **2**(3), 194–203 (2001). https://doi.org/10.1038/35058500
33. Cepeda, N.J., Cave, K.R., Bichot, N.P., Kim, M.-S.: Spatial selection via feature-driven inhibition of distractor locations. Percept. Psychophys. **60**(5), 727–746 (1998). https://doi.org/10.3758/BF03206059
34. Theeuwes, J.: Perceptual selectivity for color and form. Percept. Psychophys. **51**(6), 599–606 (1992). https://doi.org/10.3758/BF03211656
35. Steinman, B.A., Steinman, S.B., Lehmkuhle, S.: Research note transient visual attention is dominated by the magnocellular stream. Vis. Res. **37**(1), 17–23 (1997). https://doi.org/10.1016/S0042-6989(96)00151-4
36. Leuba, C.: Toward some integration of learning theories: the concept of optimal stimulation. Psychol. Rep. (1955). https://doi.org/10.2466/pr0.1955.1.g.27
37. Raju, P.S.: Optimum stimulation level: its relationship to personality, demographics, and exploratory behavior. J. Consum. Res. **7**(3), 272–282 (1980). https://doi.org/10.1086/208815
38. Steenkamp, J.-B.E., Baumgartner, H.: The role of optimum stimulation level in exploratory consumer behavior. J. Consum. Res. **19**(3), 434–448 (1992). https://doi.org/10.1086/209313
39. Baumgartner, H., Steenkamp, J.-B.E.: Exploratory consumer buying behavior: conceptualization and measurement. Int. J. Res. Mark. **13**(2), 121–137 (1996). https://doi.org/10.1016/0167-8116(95)00037-2
40. Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent Dirichlet allocation. J. Mach. Learn. Res. **3**, 993–1022 (2003)
41. Wei, X., Croft, W.B.: LDA-based document models for ad-hoc retrieval. In: Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, pp. 178–185. ACM (2006). https://doi.org/10.1145/1148170.1148204
42. Weng, J., Lim, E.-P., Jiang, J., He, Q.: Twitterrank: finding topic-sensitive influential twitterers. In: Proceedings of the Third ACM International Conference on Web Search and Data Mining, pp. 261–270. ACM (2010). https://doi.org/10.1145/1718487.1718520
43. Zhao, W.X., Jiang, J., Weng, J., He, J., Lim, E.-P., Yan, H., Li, X.: Comparing twitter and traditional media using topic models. In: Clough, P., Foley, C., Gurrin, C., Jones, G.J.F., Kraaij, W., Lee, H., Mudoch, V. (eds.) ECIR 2011. LNCS, vol. 6611, pp. 338–349. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-20161-5_34
44. Manning, C.D., Surdeanu, M., Bauer, J., Finkel, J.R., Bethard, S., McClosky, D.: The Stanford CoreNLP natural language processing toolkit. In: ACL (System Demonstrations), pp. 55–60 (2014). https://doi.org/10.3115/v1/p14-5010
45. Rhoades, S.A.: The Herfindahl-Hirschman index. Fed. Res. Bull. **79**, 188 (1993)
46. Hong, L., Davison, B.D.: Empirical study of topic modeling in twitter. In: Proceedings of the First Workshop on Social Media Analytics, pp. 80–88. ACM (2010). https://doi.org/10.1145/1964858.1964870

Exploration of the Misalignment Between Business and IT Strategic Objectives in Public-Sector Organisations: An Empirical Study in Saudi Arabia

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Abstract. Understanding business-IT strategy misalignment is an increasingly important area of research in digitalisation of different business sectors. However, there is currently a dearth of research investigations of misalignment between business and IT strategic objectives in public-sector organisations. Considering the nature of business, the structure of organisation, and the organisational resources of public-sector organisations, the investigation of business-IT misalignment can significantly enrich our theoretical exemplification of the relationship between business and IT in the public sector. Moreover, it provides some insights for managers to identify and avoid the possible pitfalls during the IT implementation process. Anchoring on the strategic alignment model, this research aims to identify and analyse the factors that contribute to business/IT strategy misalignment in Saudi Arabian public-sector organisations. Using a qualitative study design that included semi-structured interviews in five public-sector organisations in Saudi Arabia, our findings indicate that the human, operational, and IT system factors lead to business-IT strategy misalignment. This study also finds that those practical approaches for avoiding the misalignment in Saudi public-sector organisations sometimes lack structure and consistency.

Keywords: IT strategy · Business strategy · Business and IT alignment
Business and IT misalignment · Public sector · Saudi arabia

1 Introduction

The alignment between information technology (IT) strategy and business strategy is widely acknowledged as an important determinant of business success in IT-enabled organisations. By definition, misalignment between the IT strategy and business strategy is thus a key concern for managers. Business-IT misalignment is characterised as the breakdown or lack of coordination between business and IT to deliver the

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coherent management of information to meet business needs (Enagi and Ochoche 2013). Based on this definition, the misalignment is likely to negatively impact business performance given that business-IT strategy alignment is required to increase business value (e.g., Dulipovici and Robey 2013; Handley 2017; Rai et al. 2015). As stated by Fichman and Melville (2014), business performance is 'conditioned' by the business IT system.

Given the ever-increasing prevalence of IT infrastructures to support business operations in a digitalisation era, businesses across the world are increasingly required to develop and align an IT strategy with their business strategy as they seek to incorporate IT into their daily operations (Martinez et al. 2015; Seman and Salim 2013). An IT strategy is typically defined as the identification and adoption of relevant 'digital' technologies necessary to meet a set of objectives and goals by an entity (Alsudiri et al. 2013). Research on the business-IT alignment/misalignment is therefore of critical importance and an ongoing challenge within the information systems (IS) discipline (Luftman and Derksen 2012).

In recent decades, researchers have developed different models and theoretical explanations to explicate how IT alignment creates value for private sector organisations (Reynolds and Yetton 2015). The implications of these studies for operational outcomes are worthy of consideration, yet the research findings cannot be easily adopted in public-sector organisations to improve overall business performance. Indeed, the identification and measurement of strategic misalignment is made complicated by the fact that alignment is largely "unobservable" and that measuring IT and business strategy is highly complex (Tallon 2007). Hence, there are managerial concerns in the continuous failure of IT projects in public organisations (Alsudiri et al. 2013; Byrd et al. 2006) and there is increasing concern that optimal return of investment (ROI) in IT projects is not being achieved (Gerow et al. 2014; Henderson and Venkatraman 1999; Rai et al. 2015; Wu, Straub and Liang 2015). Governments would therefore benefit from further research into the main factors contributing to IT-business strategy misalignment.

The issue of IT-business strategy misalignment is important to the government of Saudi Arabia given its National e-Government strategy to improve technology-based operations and service delivery in public-sector organisations (Shehry et al. 2011; Rai et al. 2015; Yesser 2016). The implementation of the e-government project however faces many technological, cultural, organisational, and social challenges and issues, which have to be considered carefully by the Saudi government given the limited research evidence and insights on this issue to guide the successful adoption of e-government services (Bélanger et al. 2008; Shehry et al. 2011). This point is reinforced by the fact that there is no practical model available to test strategic alignment at the strategic plan level in Saudi Arabia (Alshehri and Drew 2010).

Based on the above discussion, the intent of this study is to further develop our understanding of business/IT strategy misalignments in public-sector organisations in Saudi Arabia. Towards this objective, this study aims to answer the following research question:

What are the factors leading to the misalignment between business and IT strategic objectives in public-sector organisations in Saudi Arabia?

2 Literature Review

2.1 Misalignment: An Overview

The way in which business-IT strategy misalignment is conceptualised will strongly influence the process undertaken to identify the misalignment indicators and to implement solutions (Tallon 2007). Schniederjans and Cao (2009), for instance, conceptualise misalignment as a mismatch between functional-level strategic planning and support for business-level strategies. Misalignment has also been conceptualised as a coordination issue, whereby poor coordination exists between business and IT to deliver the coherent management of information to meet business needs (Enagi and Ochoche 2013).

2.2 Sources of Business-IT Strategy Misalignment

Misalignment between an organisation's IT and strategic goals invariably emerge from the dynamics and complexities of general business practices (El-Telbany and Elragal 2014). The three broad source categories for business-IT strategy misalignment identified in the literature are: human factors (e.g., perceptions, expectations, skill levels etc.), business operation factors (e.g., knowledge assets, operational model, IT execution model etc.), and IT design factors (e.g., infrastructure components, assumptions made by IT developers).

Human Factors as a Source of Business-IT Strategy Misalignment

With regard to human factors, misalignment can occur when employees conceptualise the IT tools such as knowledge management systems (KMS) and their strategic function differently (Dulipovici and Robey 2013). This points to the need for businesses to ensure there are the appropriate mechanisms of verification to detect possible misalignments (Corsaro and Snehota 2011). Furthermore, misalignment may emerge due to differences between the social and material interactions surrounding the IT practices, particularly the use of new technology. According to Leonardi (2009), the social interactions underpin the way in which new technology is 'interpreted'; that is to say, what the technology is "meant to do". Employees' skills to manage IT effectively are also identified as a human factor leading to business-IT strategy misalignment. For instance, the skills with which employees can operate IT in combination with the outsourcing knowledge management practices initiated by managers will impact outsourcing performance and the relationship to organisational governance (Handley 2017).

Business Operational Model as a Source of Business-IT Strategy Misalignment

Enterprise architecture refers to a suite of domains such as business processes, information management, application systems and IT systems (Enagi and Ochoche 2013). Misalignment occurs when the business fails to adopt the necessary enterprise architecture to align the business and IT strategies. In turn, the extent of the misalignment/alignment between business and IT strategies can be analysed through a symptoms approach (Őri 2017). Towards this end, he proposed a model to conduct an enterprise architecture-based systematic analysis of disharmony (misalignment) between business and IT dimensions. The (IT) innovation posture of the business can also contribute to business-IT strategy misalignment when the strategic posture profile of (IT) innovation in the organisation does not match, or is not supported by, the resource profile of the organisation (Fichman and Melville 2014).

IT Solution as a Source of Business-IT Strategy Misalignment

At the IT source level, the primary focus is on the disconnection between what is assumed about business strategy objectives by IT developers and the actual business strategy objectives on the ground. For instance, when the a priori views of business managers and IT developer differ, misalignment between the IT system and business strategy is more likely because of the disconnection that emerges between the potential affordances of the IT system and the operationalisation of the capabilities (Heath et al. 2013). Wei et al. (2005) explained that misalignment between the functionality of an ERP system and the strategic objectives of the business can emerge from the 'disruptive' change dynamics necessitated through the introduction of the new system. Lastly, Soh and Sia (2004) explained business-IT misalignment from a structural perspective suggesting that it emerges due to opposing forces in the structures embedded in the IT system and the business operations. Misalignment is more likely to occur when some of the IT structures are imposed onto the organisational structures rather than voluntarily accepted, which consequently reduces the organisation's level of control over its structures leading to misalignment (Soh and Sia 2004).

Overview of Saudi Arabia Digital Government Adoption

In recent decades, IT has played a significant role in the Saudi Arabian economy. According to *The Global Information Technology Report 2015*, Saudi Arabia is ranked 35 out of 143 countries surveyed and 4.7 out of 7 in value (Dutta et al. 2015). As stated above, however, there are presently a range of technological, cultural, organisational, and social issues facing the Saudi Arabian government in its efforts to implement the adopted *National e-Government* strategy. On the other hand, although Saudi Arabia is classified as a high-income country, there is little research and insight to guide the successful to adoption of digitalised government services in Saudi Arabia (Shehry et al. 2011). Currently, there are a limited number of studies focusing on how organisations achieve the alignment between IT and business while developing or implementing IT projects. As such, there is no practical approach available to test strategic alignment at the strategic plan level in Saudi Arabia (Alshehri and Drew 2010). Studies in the field of business-IT alignment are mainly conducted in China, the United States and Australia (e.g. Al-Hatmi 2012; Al Omari and Barnes 2014). In turn, there is little empirical research provision on how to carry out alignment in a large IT project in a public-sector organisation in developing countries. Most studies focused on separate aspects and domains of the alignment model (Al Omari and Barnes 2014).

2.3 Theoretical Framework

Notably, since the 1990s, a range of models have been developed to explain and inform alignment strategies as well as to identify and/or remedy business-IT strategy misalignment. For example, the list includes, but is not limited to, the strategic alignment model (SAM) developed by Henderson and Venkatraman (1999). The SAM is an IT/business management system that enables the successful implementation of information systems/technology and businesses and their resulting infrastructural components (Renaud et al. 2016). The SAM can be based on, integrated and defined by its four core building blocks and fundamental strategic choice domains, including IT strategies, business strategies, organisational process and infrastructure and the informational systems and technologies processes and infrastructure (Luftman 2000). Each domain and feature behind the building blocks of the SAM has significance and features that mainly consist of three components, i.e., strategic fit, cross-dimension alignment and functional integration. According to Luftman and Jerry (2000), the components and features that form the components and basis of business and IT strategic alignment are the twelve components of alignment. This model emerged as one of the top business and IT alignment tools used by scholars and experts seeking to achieve business-IT alignment (Renaud et al. 2016). Therefore, applying SAM model might be presented as a logic diagram, a visual representation of relationships among the alignment between business and IT and to investigate the factors that may lead to business-IT strategy misalignment.

Notwithstanding the differences in the above mentioned conceptualisations of misalignment, the literature invariably points to three main sources of business-IT misalignment.

2.4 Methodology

Qualitative research is essentially dialectic with a core goal to reveal the truth about the research phenomenon through the analysis of data for the identification of salient themes and concepts (Benton 2014). This research philosophy was applied to explore the above research question in relation to different public-sector organisations in Saudi Arabia.

Study Design

Qualitative research paradigms were applied for this study as they support a deep-level of understanding of the research problem from the participants' perspectives (Creswell 2013). Additionally, the paradigms provide a flexible way to collect, analyse, and interpret the research data. Furthermore, using primary and unstructured data gives qualitative research a descriptive capability (Creswell 2013).

Study Sample

The sample included eight senior and executive managers in IT and business at multiple public-sector organisations in Saudi Arabia. The different job descriptions of the participants included business strategy officers, project managers, IT department managers and strategy-management offices with the governance unit. Participant recruitment was limited to senior managers or above because of their background and experiences in formulating business and IT strategic goals and objectives.

Data Collection

Semi structured interviews were conducted with eight managers from the selected organisations. Table 1 summarises the participant details[1]:

[1] Participant anonymity and data were achieved by assigning codes rather than names during the duration of the study to ensure the privacy of any given information.

Table 1. Interview participants' job titles

Job titles	Abbr.	Department	Experience
Business Development Manager	BDM	IT	15 Year
Business Development Manager	BDM	IT	13 Year
Applications Department Director	ADD	IT	23 years
Strategy Analyst	SA	Business	6 years
Business Architecture	BA	Business	25 years
Directorate of Communications	DCIT	IT	21 years
Director IT Infrastructure	DII	IT	25 years
Business Strategy Consultant	BSC	Business	20 years

The interview schedule included 13 open-ended questions intended to elicit views and opinions from the participants related to business-IT strategy and the potential factors contributing to strategy misalignment. The interviews were conducted via telephone interviews and email. With the participants' consent, the phone interviews were recorded to facilitate the data analysis process.

Data Analysis

The data was analysed using NVivo. The program supported an inductive content analysis to identify the prominent themes in the qualitative data set (Creswell 2013). A theme was defined as a recurring topic or suggested meaning in the interviewees' comments related to the main components of the research question (Clarke and Braun 2013).

3 Results

Most participants acknowledged the importance of aligning business strategies with IT strategies to improve business performance. In turn, participants' responses also revealed they perceived there to be eight factors that contribute to business-IT strategy misalignment. These factors are grouped below into the broader category sources of misalignment established above:

1. Human factors

- Lack of employee awareness and support from business decision makers (BDM)

Dulipovici and Robey (2013) found human factors to be a significant contributor to misalignment, primarily due to different employee perceptions and expectations of the IT system. The results of the data analysis also pointed to the relationship between the qualifications and actions of employees within the organisation and the realisation of desired IT strategic outcomes.

Staff qualifications and training were identified as important factors to impact business-IT strategic alignment, for example, one of the interviewees indicated:

"Most of the key IT staff members have sufficient training and qualifications". (DII)

However, three managers also indicated that there was no clear plan in their organisation to improve the skills of IT staff to meet the organisation's needs:

"There is no clear plan to improve the skills of employees to meet the needs of the organisation". (ADD)

Employee skills typically represent a critical success factor (CSF) in an organisation, particularly the skills of the CEO and IT managers (Coltman et al. 2015). As such, the findings indicate that the participants perceive the IT training provided to employees as weak; in other words, it does not provide them with sufficient skills and qualifications to support effective business-IT strategy alignment.

Furthermore, three participants indicated that the IT projects in their organisations were not underpinned by employees' clear understanding of processes, procedures and governance regulations during project lifecycle. In contrast, two participants indicated that each IT project in their organisation was governed by a steering committee comprising of various stakeholders, another participant also reported that acceptance criteria were established for IT projects in the company that identify and evaluate the achievement of key milestones to ensure continuous alignment with business needs.

2. Business operational model

- Lack of coordinated communication (SA, BA)
- Unclear requirements and responsibilities (SA)
- Unrealistic requirements and expectations from the business (BA, SA)
- Lack of clear business objectives (BDMs & ADD)

Nigeria et al. (2013) found that factors related to business operation also contributed to business-IT misalignment through the failure by the business to implement the necessary enterprise architecture to align the business and IT strategies. In turn, some managers indicated the importance of clearly stated business goals and objectives to support agile and flexible IT infrastructures, and of having regular auditing of processes, for example one of the BDMs comments:

"Developing clear and solid strategy and objectives, and developing mature KPIs to measure the alignment level" (BDM).

The finding in this study concerning a relationship between operational audits of IT system KPIs and business-IT alignment/misalignment, is also supported in other research studies. Ayoup et al. (2016) conducted a case study of a large Malaysian Government-Link Company and found that audits and reviews of the IT system KPIs using the balanced scorecard (BSC) approach supported improvement in operational processes.

In addition, most managers believed there was not a sufficiently effective approach or method in place in their organisation to measure the profit-driven traditional, ROI and the limit of optimum project profitability:

"Generally, our origination does not have a dependable and clear approach to measuring ROI in public organisations". (ADD)

The finding of an inconsistent approach by organisations to measuring the profit-driven traditional, ROI, and the limit of optimum project profitability suggests a lack of synchronisation between business processes and business objectives leading to business turbulence (Melnyk et al. 2014).

The manager participants also varied in their views on the pattern of engagement with IT innovation in their organisation and how it was aligned with the broader organisational strategy to improve profit and performance outcomes. Some participants pointed to an automated approach; whereas others indicated that their organisation did not have an overall innovation plan or a rule for IT-led innovation, for instant two of participants commented:

"Automating all manual processes where applicable and keeping up to date with the latest technology to eliminate legacy processes where possible". (DII)

"Our origination does not have innovation strategy. Questionnaires have been used to collect new ideas from the employees". (ADD).

In terms of IT and innovation strategy, the findings in this study correlate with those presented by Fichman and Melville (2014) that misalignment between an organisation's position on IT innovation and its IT innovation resource profile shapes the relationship between IT innovation and the performance of the organisation.

In terms of the organisation's use of specific frameworks to avoid and detect misalignment between the enterprise architecture, the primary business objectives, and the level of engagement between the business and IT domains, the participants varied in their responses. For instance, one BSC spoke about the use of TOGAF and enterprise architect; whereas, another BDM described how his organisation had a committee comprised of sectors head, who was responsible for ensuring that all decisions were aligned also with the organisation's goals and objectives.

Also, organisations were found to use varied approaches to managing risks related to business-IT misalignment. This is consistent with other studies. Hinkelmann et al. (2016, p. 78) assert the effectiveness of the TOGAF enterprise architecture framework in an organisation to "continuously monitor itself and be prepared to react quickly to threads and opportunities". As (Őri 2017) explains, the identification, examination and correction of misalignment can be accomplished through the utilisation of the enterprise architecture model.

3. IT solutions

- Lack of IT agility (BA)
- Legacy systems not aligned to any of the IT standards or best practices (DII)
- When IT adopts the rule of planning and accountability instead of business (BSC)

Prior research also shows the IT system itself can be a contributing factor to business-IT misalignment. Most respondents confirmed that there was not a suitable enterprise architecture framework dedicated for use in their company:

"Our origination does not use any kind of architecture frameworks". (ADD)

The Saudi organisations generally do not employ an Enterprise Architecture framework to achieve core business objectives, as consistent with the finding reported by Alshathry (2016). Specifically, the same author reported that there was a "sharp disjoint between IT and business strategy" in Saudi organisations due to a lack of maturity in their understanding of business process management and the utilisation of relevant measurement tools (Alshathry (2016, p. 507).

However, some participants added that they were using the customised The Open Group Architecture Framework (TOGAF) to manage enterprise architecture along with Software Development Life Cycle (SDLC) to ensure consistent delivery of IT application and projects:

"Our IT organisation is aligned to Information Technology Infrastructure Library (ITIL) best practices, and complies with ISO 20 K standards, and we have an enterprise BMC solution aligned to all ITIL V3 processes". (DII)

In terms of the organisation's IT strategy for performance appraisal, three participants indicated that the organisation's IT KPIs were reviewed every quarter, and one participant indicated that the organisation's IT projects included two KPIs: average issue resolution time, and system availability. Another participant commented that IT project KPIs were reviewed by the board to agree on corrective actions or to implement new projects.

As stated by one participant, *"KPIs are an essential component to manage the organisation and to provide an objective tool to measure progress in achieving the enterprise strategy. Strategic level KPIs are cascaded into department and project scorecards, which are then rolled up to measure the actual performance of our organisation as-a-whole. The IT strategy scorecard includes various objectives and KPIs to measure different perspective such as internal growth, process efficiencies, and financial contribution. (BA)"*

Regarding the organisation's use of technology solutions to share knowledge and information, most participants revealed that their organisation was using SharePoint software:

At the department level, we are using MS SharePoint and Document library. (BA)

The finding that technology-based solutions for knowledge management are used in the Saudi organisation reflects current commentary in the literature. For instance, Khaled et al. (Khaled et al. 2017) claims that the Saudi government is actively pursuing initiatives to implement Knowledge Management (KM) tools, methods and philosophies in public-sector organisations to improve operational outcomes.

Some participants (ADM and BSC) acknowledged that their organisation did not apply specific control procedures or standards at their organisations. One participant however indicated that implementing IT projects involves the application of global standard procedures, and rules and methodologies to accommodate those standards. In addition, two participants stated that their IT service management solution complies with ITIL V3 Standards and all its processes are based on ITIL best practices.

In sum, when considered collectively, the factors contributing to business-IT misalignment identified by the participants cover a wide range of operational aspects including the clarity of the business and IT objectives; communication pathways; employee knowledge and skills; the agility of internal control mechanisms (e.g., policies, procedures); and the nature of the expectations placed upon the IT systems. As such, the results identify human, business and IT factors as potential sources of IT-business strategy misalignment. The participants' views confirmed that a few well-known but diverse factors contribute to business-IT strategy misalignment.

4 Discussion

The primary objective of this study is to answer what are the factors leading to the misalignment between business and IT strategic objectives in public-sector organisations in Saudi Arabia. The main finding to emerge from the analysis of data is that misalignment between the business and IT strategy objectives in Saudi public-sector organisations can emerge as a result of human, operational, and/or IT systems issues, and that the avoidance or remedy of misalignment issues requires a well-structured and model-based misalignment detection processes. Furthermore, when seeking to properly align business and IT objectives it is crucial for Saudi organisations to ensure employees have a good understanding of the capabilities of the IT systems and how such capabilities can be optimised to achieve the core business goals and objectives.

This finding suggests the importance of a coordinated and sophisticated approach by Saudi public-sector organisations to manage business-IT misalignment issues and outcomes. Given that lack of employee awareness and support from business decision makers emerged as a human factors source of business/IT strategy misalignment in the Saudi public-sector organisations, it is arguably the case that organisations need to consider human resource management issues and how they manage social interactions to facilitate optimal IT system use outcomes. Employees' knowledge of the system and their expectations of how the IT system contributes to the achievement of core business goals and objectives are of particular importance (Dulipovici and Robey 2013). In turn, one of the implications for practice is the need in Saudi organisations to incorporate more informal workplace training activities into operational practices to better deliver the anticipated benefits of the IT systems (Esteves 2014).

In addition, the findings in this study of inefficiencies in the business operational models of the Saudi organisations related to lack of clear business objectives and unrealistic managerial expectations of IT systems and infrastructures points to the need for the organisations to improve their approaches to IT utilisations. As Enagi and Ochoche (2013) point out, as business goals objective are adjusted or modified, so must the technological architectures be modified. Furthermore, a related implication for practice is the increasing need for organisations to ensure the regular audit or review of the IT systems for their alignment with business objectives. Audits and reviews in this context are crucial to managerial decision making as they provide managers with a basis by helping them to clarify their strategic objectives, measures, and targets (Aversano et al. 2012; Ayoup et al. 2016).

Governance structures and processes in an organisation can significantly impact the successful implementation of IT projects (Wu et al. 2015). Regarding control procedures, Saudi organisations attempt to achieve strategic alignment through a range of internal control mechanisms. Similarly, Cram et al. (2016) also found that organisations used a range of control mechanisms to address four core IT control dimensions: the IT system environment, the control mechanism itself, socio-emotional behaviours of employees, and the execution of control procedures. Notwithstanding the heavy investment in IT by the Saudi Arabian government in all public-sector organisations, many organisations are still not able to allocate sufficient management, operational and governance resources towards the implementation of IT projects.

Lastly, the findings of a lack of IT agility and misalignment between the legacy systems and IT standards suggest more efficient and effective use of misalignment detection and remedy models and frameworks are needed. This will facilitate better business-IT strategic alignment in Saudi public-sector organisations. Therefore, stakeholders' expectations for quality product and service delivery from these organisations, along with the organisation's priority to achieve key goals and objectives, should dictate that greater attention must be paid by the Saudi government to implementing and properly utilising suitable IT systems and platforms.

5 Conclusion

It is well-established that IT and business strategic misalignment is a critical and fundamental issue of concern to both executives and IT professionals in contemporary organisations around the world. In Saudi Arabia, specifically, executive staff and IT managers are under increasing pressure to support the service quality and sustainability of the organisation by avoiding and remedying business-IT misalignment issues. This study identified the human, operational, and IT system factors that contributed to misalignment between business and IT strategic objectives in Saudi public-sector organisations. As a result, well-structured and continuous efforts are required by managers and IT staff in Saudi organisations to eliminate misalignment and thus optimise organisational performance. Towards this outcome, employees at all levels must have a sound knowledge of the goals and objectives of the business operations and understand the role IT playing in supporting their achievement.

5.1 Theoretical Contribution

This study contributes to our academic and practical understanding of business-IT strategy misalignment through its analysis of the main causal factors of IT and business misalignment and their implications for organisational performance. Also, in order to and investigate the most important attribute and perspective to verify the alignment between IT and business by exploring the misalignment factors to improve IT and business strategy alignment, a growing up number of studies have examined public organizational performance. However, there have been very limited researches that had examined the misalignment particularly in devolving countries public sector. Thus, this empirical study in Saudi Arabian public sector will enhance the development of misalignment models and theories and develop set of interviews questionnaires to capture the factors that truly affect to IT and business strategy misalignment.

5.2 Practical Contribution

This study tried to contribute preliminary knowledge in the following areas: the factors influencing IT performance and misalignment between IT strategy and business strategy by examining Business-IT alignment maturity in public-sector organisations, as a special case, in Saudi Arab; the operational measures utilised in organisations to promote alignment and avoid misalignment; the perspectives and attributes of misalignment as revealed in a synthesis of the relevant research and academic literature on business-IT strategy misalignment and its implications for organisational performance. Also, our work would help executives and senior managers to improve business performance.

5.3 Limitations and Future Research

As a qualitative study, the generalisability of the study findings might be limited. Consequently, research studies with a much larger sample size are required to ensure appropriate generalisation of this study's findings. The suggestion for future research is that subsequent research investigations in the field of business-IT misalignment include a larger sample size that represents more diverse aspects of the organisation's operations. Specifically, future research studies should include employees from all levels of authority in the organisation and with diverse roles and responsibilities to facilitate a holistic and whole-of-organisation analysis of business-IT misalignment and its implications for operations.

References

Al-Hatmi: Analysis of ICT Strategic Alignment in a Public Organisation. Doctor of Philosophy, Faculty of Business, Bond University, Australia (2012)

AlShathry, O.: Business process management: a maturity assessment of Saudi Arabian organizations. Bus. Process Manage. J. **22**, 507–521 (2016)

Alshehri, M., Drew, S.: Challenges of e-government services adoption in Saudi Arabia from an e-ready citizen perspective. World Acad. Sci. Eng. Technol. **66**, 1053–1059 (2010)

Alsudiri, T., Al-Karaghouli, W., Eldabi, T.: Alignment of large project management process to business strategy: a review and conceptual framework. J. Enterp. Inf. Manage. **26**, 596–615 (2013)

Al Omari, L., Barnes, P.: It governance stability in a political changing environment: exploring potential impacts in the public sector. J. Inf. Technol. Manage. **25**(3), 41–52 (2014)

Aversano, L., Grasso, C., Tortorella, M.: A literature review of business/IT alignment strategies. Procedia Technol. **5**, 462–474 (2012)

Ayoup, H., Omar, N., Rahman, I.: Balanced scorecard and strategic alignment: a Malaysian case. Int. J. Econ. Financ. Issues **6**(4S), 685–695 (2016)

Bélanger, F., Carter, L.: Trust and risk in e-government adoption. J. Strateg. Inf. Syst. **17**(2), 165–176 (2008)

Benton, T.: Philosophical foundations of the three sociologies (RLE Social Theory). Routledge, London (2014)

Clarke, V., Braun, V.: Teaching thematic analysis: overcoming challenges and developing strategies for effective learning. Psychologist **26**(2), 120–123 (2013)

Byrd, T.A., Lewis, B.R., Bryan, R.W.: The leveraging influence of strategic alignment on IT investment: an empirical examination. Inf. Manag. **43**(3), 308–321 (2006)

Coltman, T., Tallon, P., Sharma, R., Queiroz, M.: Strategic IT alignment: twenty-five years on. J. Inf. Technol. **30**(2), 91–100 (2015)

Corsaro, D., Snehota, I.: Alignment and misalignment in business relationships. Ind. Mark. Manage. **40**(6), 1042–1054 (2011)

Cram, W.A., Brohman, M.K., Chan, Y.E., Gallupe, R.B.: Information systems control alignment: complementary and conflicting systems development controls. Inf. Manag. **53**(2), 183–196 (2016)

Creswell, J.W.: Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. Sage Publications (2013)

Dulipovici, A., Robey, D.: Strategic alignment and misalignment of knowledge management systems: a social representation perspective. J. Manage. Inf. Syst. **29**(4), 103–126 (2013)

Dutta, S., Geiger, T., Lanvin, B.: Global information technology report 2015: ICTs for inclusive growth. World Economic Forum, Geneva, Switzerland (2015)

El-Telbany, O., Elragal, A.: Business-information systems strategies: a focus on misalignment. Procedia Technol. **16**(2), 250–262 (2014)

Enagi, M.A., Ochoche, A.: The role of enterprise architecture in aligning business and information technology in organisations: Nigerian government investment on information technology. Int. J. Eng. Technol. **3**(1), 59–65 (2013)

Esteves, J.M.: An empirical identification and categorisation of training best practices for ERP implementation projects. Enterp. Inf. Syst. **8**(6), 665–683 (2014)

Fichman, R.G., Melville, N.P.: How posture-profile misalignment in IT innovation diminishes returns: conceptual development and empirical demonstration. J. Manage. Inf. Syst. **31**(1), 203–240 (2014)

Gerow, J.E., Grover, V., Thatcher, J.B., Roth, P.L.: Looking toward the future of IT-business strategic alignment through the past: a meta-analysis. MIS Q. **38**(4), 1059–1085 (2014)

Handley, S.M.: How governance misalignment and outsourcing capability impact performance. Prod. Oper. Manage. **26**(1), 134–155 (2017)

Heath, D., Singh, R., Shephard, B.: Approaching strategic misalignment from an organizational view of business processes. In: 2013 46th Hawaii International Conference on System Sciences (HICSS), pp. 4055–4064. IEEE (2013)

Hinkelmann, K., Gerber, A., Karagiannis, D., Thoenssen, B., Van der Merwe, A., Woitsch, R.: A new paradigm for the continuous alignment of business and IT: combining enterprise architecture modelling and enterprise ontology. Comput. Ind. **79**(2), 77–86 (2016)

Henderson, J.C., Venkatraman, H.: Strategic alignment: leveraging information technology for transforming organizations. IBM Syst. J. **32**(1), 472–484 (1999)

Khaled, A., Renukappa, S., Suresh, S., Saeed, A.: Knowledge management practices in Saudi Arabian public sector organisations: a case of the ministry of justice. In: Benlamri, R., Sparer, M. (eds.) Leadership, Innovation and Entrepreneurship as Driving Forces of the Global Economy. SPBE, pp. 445–459. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-43434-6_39

Leonardi, P.M.: Why do people reject new technologies and stymie organizational changes of which they are in favor? Exploring misalignments between social interactions and materiality. Hum. Commun. Res. **35**(3), 407–441 (2009)

Luftman, J.: Assessing business-IT alignment maturity. Commun. Assoc. Inf. Syst. **4**(14), 9–15 (2000)

Luftman, J., Derksen, B.: Key issues for IT executives 2012: doing more with less. MIS Q. Executive **11**(4), 207–218 (2012)

Melnyk, S.A., Bititci, U., Platts, K., Tobias, J., Andersen, B.: Is performance measurement and management fit for the future? Manage. Acc. Res. **25**(2), 173–186 (2014)

Martinez-Simarro, D., Devece, C., Llopis-Albert, C.: How information systems strategy moderates the relationship between business strategy and performance. J. Bus. Res. **68**(7), 1592–1594 (2015)

Őri, D.: On exposing strategic and structural mismatches between business and information systems: misalignment symptom detection based on enterprise architecture model analysis. PhD thesis, Corvinus University, Budapest (2017) http://phd.lib.uni-corvinus.hu/964/. Accessed 23 Aug 2014
Rai, A., Arikan, I., Pye, J., Tiwana, A.: Fit and misfit of plural sourcing strategies and IT-enabled process integration capabilities: consequences of firm performance in the US electric utility industry. MIS Q. **39**(4), 865–885 (2015)
Renaud, A., Walsh, I., Kalika, M.: Is SAM still alive? A bibliometric and interpretive mapping of the strategic alignment research field. J. Strateg. Inf. Syst. **25**(2), 75–103 (2016)
Reynolds, P., Yetton, P.: Aligning business and IT strategies in multi-business organizations. J. Inf. Technol. **30**(2), 101–118 (2015)
Schniederjans, M., Cao, Q.: Alignment of operations strategy, information strategic orientation, and performance: an empirical study. Int. J. Prod. Res. **47**(10), 2535–2563 (2009)
Shehry, A.A., Rogerson, S., Fairweather, N.B., Prior, M.: The key organisational issues affecting e-government adoption in Saudi Arabia. In: Weerakkody, V. (ed.) Applied Technology Integration in Governmental Organizations: New e-Government Research, pp. 257–269. Information Science Reference, New York (2011)
Seman, E.A.A., Salim, J.: A model for business-IT alignment in Malaysian public universities. Procedia Technol. **11**, 1135–1141 (2013)
Soh, C., Sia, S.K.: An institutional perspective on sources of ERP package–organisation misalignments. J. Strateg. Inf. Syst. **13**(4), 375–397 (2004)
Yasser e-government program. The national strategy and the e-government action plan. http://www.yesser.gov.sa/en/MechanismsandRegulations/strategy/Pages/default.aspx. 15 Oct 2016
Tallon, P.P.: A process-oriented perspective on the alignment of information technology and business strategy. J. Manage. Inf. Syst. **24**(3), 227–268 (2007)
Wei, H.L., Wang, E.T., Ju, P.H.: Understanding misalignment and cascading change of ERP implementation: a stage view of process analysis. Eur. J. Inf. Syst. **14**(4), 324–334 (2005)
Wu, S.P.J., Straub, D.W., Liang, T.P.: How information technology governance mechanisms and strategic alignment influence organizational performance: insights from a matched survey of business and IT managers. MIS Q. **39**(2), 497–518 (2015)

Influences of Place Attachment and Social Media Affordances on Online Brand Community Continuance

(Research-in-Progress)

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Abstract. Online brand communities not only enhance customer loyalty and experience but also help in building a closer relationship among brands, suppliers, and other customers, contributing to a healthy and positive identification. Moreover, the emergence and rapid development of social media have brought customers to become an indispensable part of brand activities through conversation and co-creation with the brand. Factors that affect customers' intentions for continual participation in online brand communities thus present a research opportunity to be explored as well as a research gap to be filled. Drawing on the place attachment theory and social media affordances perspectives, which serve as contextual and instrumental drivers, respectively, this research investigates the influence of place attachment and social media affordances on online brand community continuance. In addition, the mediating role of experience and brand engagement will be addressed in order to build a more holistic model on the causal relationships. The ultimate goal is to help us build a clearer picture of customers' participation behavior in online brand communities.

Keywords: Online brand community · Service experience · Brand engagement Place attachment · Social media affordances · Continuance intention

1 Introduction

Brand communities not only enhance customer loyalty and experience but also help in building a closer relationship among brands, suppliers, and other customers, contributing to a healthy and positive identification (Algesheimer et al. 2005; McAlexander et al. 2002). Prior studies on technology adoption and continuance, however, have primarily focused on the technology-user view. The role of service experience in

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providing the view of service consumers, however, has been neglected (Kim et al. 2007), and thus presents a research gap to be filled. Service experience is especially important because online brand communities are not only a technology platform that provides utilitarian or hedonic value to its members but also a service tool to maintain close relationship between brands and customers to co-create value through continual participation. One other important factor that affects the success of online brand communities is brand engagement. Consumer brand engagement benefits social word-of-mouth as a form of co-creation activity (Brodie et al. 2011, 2013) in online brand communities.

Following the logic above, one question emerges: If experience and brand engagement are two important factors that determine continuance intentions in online brand communities, what are the antecedents that determine the quality of these two factors? This study intends to investigate and integrate influences of both context and instrument. The former refers to the meaning online brand communities have for its participants, and the latter regards how social media are used to expand and deepen the influence of online brand communities. The perspectives of place attachment and social media affordances, respectively, have therefore been adopted as the theoretical foundations that this research draws on.

The concept of place attachment originated from environmental psychology research. Through a series of events, content sharing, and interactions happening in the community, participants would endow the space with value. Such interactional process turns the abstract space into a meaningful place and leads to personal experiences (Goel et al. 2011) and emotional connections (Hernández et al. 2007; Hidalgo and Hernández 2001) deeply attached to that place. It is through the idea of place attachment that online brand communities justify its meaning and value and thus create unique experiential value and customer engagement during the interactional process.

Social media affordances represent the instrumental characteristics of the media platform that brands utilize for online brand communities. Treem and Leonardi (2012) pointed out that visibility, persistence, editability, and association are four salient technological properties of social media that afford user communication and interaction. These four properties have been considered instrumental enablers that foster online brand community experiences on social media. This research thus intends to examine the link between social media affordances and experiences as well as brand engagement.

Customers have become an indispensable part of brand activities through conversation and co-creation with the brand. Therefore, how place attachment and social media affordances affect customers' intentions for continual participation in online brand communities presents a research opportunity to be explored as well as a research gap to be filled. In addition, the mediating role of experience and brand engagement will be addressed in order to build a more holistic picture of customers' participation behavior in online brand communities.

2 Theoretical Foundation and Literature Review

2.1 Place Attachment Theory

Place attachment is one's emotional connection with a place (Hidalgo and Hernandez 2001) and requires one's experience with the place and social interaction (Rubinstein and Parmelee 1992). Interaction refers to how things existing and occurring in the place influence people in it (Goel et al. 2011). Being aware of the environment through sensory inputs, one attends to informational inputs and attaches meanings by engaging with selective sensory inputs. Such interaction leads to positive emotional connection with the place (Tuan 1977).

Sense of place emerges when one can distinguish one place from the other or describe the characteristics pertaining to a particular place (Relph 1976). Sense of place develops into place attachment in three stages. In the first stage, sense of place emerges through one's contact with the place. In the second stage, identification to a place either intensifies through insideness or weakens because of outsideness. In the third stage, intensified identification with the place generates place attachment, whereas weakened identification leads to place detachment (Relph 1976).

Using a lab experiment, Goel et al.'s (2011) study found that cognitive absorption, jointly determined by social awareness, location awareness, and task awareness, determines virtual world users' intentions for returning. Social awareness is defined as "the perception a person has that she and others in the same space find it easy to understand and interact in a social sense" (p. 753), meaning that when an interaction is underway in the online brand community, one can be aware whether other users are available for socially accepted interactions. Location awareness regards the features of a virtual environment in which users are aware of where he or she is in relation to objects in the environment (Baecker et al. 1993; Goel et al. 2011). Task awareness is defined as "the perception a person has about what she is to do based on instructions, tools, or the actions of others in a given shared space" (p. 753).

To make members feel attached to an online brand community, it is important that brand companies need to let members know what the community is for (connection with the brand), feel the warmth and vitality of the interactions, and be assured that problems regarding the products and services can be solved effectively. Although brand communities exist in the virtual environment, activities, interactions, and information sharing happening in the communities make brand communities a right candidate for being "a meaningful place" for its members. This research thus draws on the place attachment theory to investigate the influence of place attachment on brand community continuance intention, through the mediation of experience and brand engagement.

2.2 Social Media Affordances

The concept of affordances can be traced back to the studies of Gibson (1977, 1979). As indicated by Treem and Leonardi (2012), "[a]ffordances are unique to the particular ways in which an actor, or a set of actors, perceives and uses the object" (p. 145). Norman (1988) regarded affordances as the perceived and actual properties of the object which suggests how the object could possibly be used. According to Norman (1988), affordances provide cues for possible usage of objects, and the very basic features of an object determine how the object could be used.

Research on affordances provides a different view, in contrast to the traditional functional and quality features, for researchers to investigate the influence of new technologies. An example of the new technology under investigation is social media, which have created new ways of connection, collaboration, and innovation with customers (Cisco 2010; Dunn 2010; Wilson et al. 2011).

The four social media affordances proposed by Treem and Leonardi (2012), namely visibility, persistence, association, and editability, have been widely adopted by social media researchers. With the affordance of visibility in social media, social media users' behavior, knowledge, preferences, and connections become visible to others. Social media, however, improved the visibility of behavior and information (Grudin 2006; Boyd 2010) and makes user posts, comments, status updates, votes, friend networks, and pictures available to those who have authorized access. Moreover, because of the visibility affordance, customers are able to notice, and track, status updates and ongoing activities related to specific brands they follow.

Persistence allows user-created and published content be available and accessible to other users, even when the original publisher is offline, and is also known as reviewability (Clark and Brennan 1991), recordability (Hancock et al. 2007), or permanence (Whittaker 2003). Because social media provides the possibility of permanent access, content and conversations can be searched, browsed, replayed, annotated, visualized, restructured, and recontextualized (Erickson and Kellogg 2000), thus enabling communicative actions with lasting influences.

Editability retains user control over communicative content by allowing users to create, modify, and reproduce content that they post in social media. Hence, the idea of the editability affordance is similar to rehearsability proposed by Denis et al. (2008), indicating that social media users are able to conduct purposeful and accurate communication. By employing the editability affordance, social media users become aware of how other users react to their posts and comments and can manipulate communicative content in response.

With the affordance of association, social media allows users to build connections with other users and with content. Connection with other users can be established through friending, following, or subscribing to others. Connection with content is built through contributing, tagging or liking (or, for example, "+1" in Google+ and "♡" in Instagram). The affordance of association allows and supports users to gain access to other users they have social connection with as well as to content they associate with.

2.3 Service Experience

In contrast to traditional theme parks, which provide recreation values through ticket selling and entertaining facilities, Disney Parks create experiences deeply connected to our childhood memories that make visitors easily fall into and become deeply immersed during visiting. This demonstrates the value-in-use of Disney Parks, where the visitor and his/her childhood memory constitute part of the unique experience. This research thus intends to draw on the service-dominant logic perspective to investigate the role of service experience in continual participation in brand communities.

Prior studies have indicated service experience as the outcome of the memorable process of co-creation between customers, service providers, and value creation partners (Kim et al. 2012; Pine and Gilmore 1999; Poulsson and Kale 2004). Besides being memorable, service experience could occur at any conscious moment in any given individual (Pine and Gilmore 1999; Poulsson and Kale 2004). According to Pine and Gilmore (1999), "the newly identified offering of experiences occurs whenever a company intentionally uses services as the stage and goods as props to engage an individual" (p. 10). Poulsson and Kale (2004) described commercial experience as "an engaging act of co-creation between a provider and a consumer wherein the consumer perceives value in the encounter and in the subsequent memory of that encounter" (p. 270). An experience is phenomenological in nature (Pine and Gilmore 1999; Poulsson and Kale 2004; Vargo and Lusch 2008). Wang's (2015) study justified the mediating role of service experience in mobile value-added service continuance when users play duals role of technology users as well as service consumers.

2.4 Brand Engagement

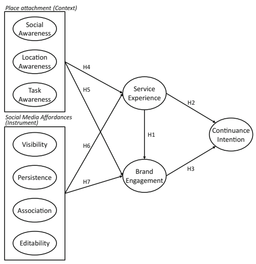
Engagement and involvement are commonly-adopted constructs for the study of consumer intention and behavior (e.g., Hsieh and Chang 2016; Park et al. 2007). In contrast to the focus of involvement on personal relevance (Rothschild 1984; Zaichkowsky 1985), brand engagement is a psychological state, psychological process, transcendent, interactive experiences, or patterns of engagement activities of customers that occurs as a result of the interactive experiences with a brand (Brodie et al. 2013).

Brand engagement is a key issue in online brand community research because online brand communities reflect brand companies' endeavor to expand and intensify their influences through the online channel. The aim is to enhance the values of brands, products, services, and experiences by turning customers into indispensible parts of brand activities (Füller et al. 2007; Nambisan and Nambisan 2008). Therefore, researchers have further extended the foundation set forth by earlier research on brand engagement by considering how brand co-creation engagement, defined as "a persistent, positive affective-motivational state of fulfillment that is characterized by vigor, dedication, and absorption toward brand co-creation" (p. 15), leads to a strengthened consumer-brand relationship (Hsieh and Chang 2016).

The conceptualization of brand engagement in literature as a psychological state captures the cognitive, emotional, and behavioral dimensions of consumer-brand interactions, including relevant cognitive processing, affection, and activation (Hollebeek et al. 2014). Researchers have also devoted to the measurement of brand engagement. Hollebeek et al.'s (2014) work suggested a three-dimensional structure, which includes the subdimensions of cognitive processing, affection, and activation to measure consumer brand engagement in social media. Other researchers such as Erdoğmuş and Tatar (2015), Hollebeek (2011), and Van Doorn et al. (2010) have also proceeded with the multidimensional attempt to measure brand engagement. Algesheimer et al. (2005), attempted to measure brand community engagement in utilitarian, hedonic, and social aspects.

3 Research Model and Hypotheses

Drawing on the place attachment theory and social media affordances perspectives, which serve as contextual and instrumental drivers, respectively, this research investigates whether and how service experience and consumer brand engagement mediate the influence of place attachment and social media affordances on online brand community continuance. The model shown in Fig. 1 depicts the integrative attempt and the associated research hypotheses.



H1: Service experience associated with an online brand community positively influences community participants' brand engagement.
H2: Service experience associated with an online brand community positively influences community participants' continuance intention.
H3: Online brand community participants' brand engagement positively influences participants' continuance intention.
H4: Place attachment awareness positively influences the service experience associated with an online brand community.
H5: Place attachment awareness positively influences online brand community participants' brand engagement.
H6: Social media affordances positively influence the service experience associated with an online brand community.
H7: Social media affordances positively influence online brand community participants' brand engagement.

Fig. 1. Research model

Online brand community participants play the roles of not only technology users but also service consumers (AlHinai et al. 2007; Kim et al. 2007). Prior research has emphasized the role of experience in brand management and technology continuance (e.g., Brakus et al. 2009; Wang 2015). The current research not only echoes the line of research on technology continuance but also makes significant contribution to IS and marketing literature by integrating the multidisciplinary perspective into online brand community research. By incorporating place attachment and social media affordances, the research model also indicates the mediating role of online brand community experience and brand engagement on the relationship between both place attachment and social media affordances and continuance intention for participation in online brand communities.

4 Research Methodology

Survey approach will be the primary method for data collection. The online mode of data collection, characterized by its expediency in data collection, ease of data tabulation, and ability to reach a wide population of users (Bhattacherjee 2002), will be conducted, targeting at Internet users who have experiences in online brand community participation. The online mode of data collection will reduce the possible bias of distributing paper questionnaires, which often confines respondents to a smaller group of people in specific physical locations. Moreover, because the theme of this research is on continual participation in online brand communities, online survey is deemed appropriate for the research purpose and context.

To ensure the face validity and content validity of the questionnaire, the draft version will be reviewed by field experts and online brand community participants. The purpose of this pretest phase is to ensure the appropriateness and readability of the final questionnaire. Modifications in semantic wording or expression will proceed, following the suggestions we receive. Based on the comments and suggestions, the questionnaire will be improved in terms of clarity and readability and adopted for the online survey. After the questionnaire is finalized, a pilot test will be carried out to test the quality of the instrument. The identities of the pilot test participants will be recorded and excluded from the final survey.

References

Algesheimer, R., Dholakia, U.M., Herrmann, A.: The social influence of brand community: evidence from European car clubs. J. Mark. **69**(3), 19–34 (2005)

AlHinai, Y., Kurnia, S., Johnston, R.: Adoption of mobile commerce services by individuals: a meta-analysis of the literature. In: Proceedings of the 6th International Conference on the Management of Mobile Business, Toronto, Ontario, Canada (2007)

Baecker, R.M., Nastos, D., Posner, I.R., Mawby, K.L.: The user-centered iterative design of collaborative writing software. In: Proceedings of the INTERACT 1993 and CHI 1993 Conference on Human Factors in Computing Systems, pp. 399–405. ACM (1993)

Bhattacherjee, A.: Individual trust in online firms: scale development and initial test. J. Manag. Inf. Syst. **19**(1), 211–241 (2002)

Boyd, D.: Social network sites as networked publics: affordances, dynamics and implications. In: Papacharissi, Z. (ed.) Networked Self: Identity, Community, and Culture on Social Network Sites, pp. 39–58. Routledge, New York (2010)

Brakus, J.J., Schmitt, B.H., Zarantonello, L.: Brand experience: what is it? How is it measured? Does it affect loyalty? J. Mark. **73**(3), 52–68 (2009)

Brodie, R.J., Hollebeek, L.D., Juric, B., Ilic, A.: Customer engagement: conceptual domain, fundamental propositions & implications for research in service marketing. J. Serv. Res. **14** (3), 252–271 (2011)

Brodie, R.J., Juric, B., Ilic, A., Hollebeek, L.D.: Consumer engagement in a virtual brand community: an exploratory analysis. J. Bus. Res. **66**(1), 105–114 (2013)

Cisco: Social media: cultivate collaboration and innovation. Cisco (2010). http://www.cisco.com/en/US/services/ps2961/ps2664/CiscoServicesSocialMediaWhitePaper.pdf. Accessed 5 Jan 2017

Clark, H.H., Brennan, S.E.: Grounding in communication. In: Resnick, L.B., Levine, J.M., Teasley, S.D. (eds.) Perspectives on Socially Shared Cognition, pp. 127–149. APA, Washington, DC (1991)

Dennis, A.R., Fuller, R.M., Valacich, J.S.: Media, tasks, and communication processes: a theory of media synchronicity. MIS Q. **32**(3), 575–600 (2008)

Dunn, B.J.: Best buy's CEO on learning to love social media. Harvard Bus. Rev. **88**(12), 43–48 (2010)

Erdoğmuş, İ.E., Tatar, Ş.B.: Drivers of social commerce through brand engagement. Procedia-Soc. Behav. Sci. **207**, 189–195 (2015)

Erickson, T., Kellogg, W.: Social translucence: an approach to designing systems that support social processes. ACM Trans. Comput. Hum. Interact. **7**(1), 59–83 (2000)

Füller, J., Jawecki, G., Mühlbacher, H.: Innovation creation by online basketball communities. J. Bus. Res. **60**(1), 60–71 (2007)

Gibson, J.J.: The theory of affordances. In: Shaw, R., Bransford, J. (eds.) Perceiving, Acting, and Knowing, pp. 67–82. Lawrence Erlbaum, Hillsdale (1977)

Gibson, J.J.: The Ecological Approach to Visual Perception. Psychology Press, Hove (1979)

Goel, L., Johnson, N.A., Junglas, I., Ives, B.: From space to place: predicting users' intentions to return to virtual worlds. MIS Q. **35**(3), 749–772 (2011)

Grudin, J.: Enterprise knowledge management and emerging technologies. In: Proceedings of the 39th Annual Hawaii International Conference on System Sciences, 2006, HICSS 2006, vol. 3, p. 57a. IEEE (2006)

Hancock, J.T., Toma, C., Ellison, N.B.: The truth about lying in online dating profiles. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, pp. 449–452. ACM, New York (2007)

Hernándeza, B., Hidalgob, M.C., Salazar-Laplacea, M.E., Hess, S.: Place attachment and place identity in natives and non-natives. J. Environ. Psychol. **27**(4), 310–319 (2007)

Hidalgo, C.M., Hernandez, B.: Place attachment: conceptual and empirical questions. J. Environ. Psychol. **21**, 273–281 (2001)

Hollebeek, L.: Exploring customer brand engagement: definition and themes. J. Strateg. Mark. **19** (7), 555–573 (2011)

Hollebeek, L.D., Glynn, M.S., Brodie, R.J.: Consumer brand engagement in social media: conceptualization, scale development and validation. J. Interact. Mark. **28**(2), 149–165 (2014)

Hsieh, S.H., Chang, A.: The psychological mechanism of brand co-creation engagement. J. Interact. Mark. **33**, 13–26 (2016)

Kim, H.-W., Chang, H.C., Gupta, S.: Value-based adoption of mobile Internet: an empirical investigation. Decis. Support Syst. **43**(1), 111–126 (2007)

Kim, J.H., Ritchie, J.R.B., McCormick, B.: Development of a scale to measure memorable tourism experiences. J. Travel Res. **51**(1), 12–25 (2012)

McAlexander, J.H., Schouten, J.W., Koenig, H.F.: Building brand community. J. Mark. **66**(1), 38–54 (2002)

Nambisan, S., Nambisan, P.: How to profit from a better 'virtual customer environment'. MIT Sloan Manag. Rev. **49**(3), 53–61 (2008)

Norman, D.A.: The Design of Everyday Things. Doubleday Business, New York (1988)

Park, D.H., Lee, J., Han, I.: The effect of on-line consumer reviews on consumer purchasing intention: the moderating role of involvement. Int. J. Electron. Commer. **11**(4), 125–148 (2007)

Pine, B.J., Gilmore, J.H.: The Experience Economy: Work Is Theater and Every Business a Stage. Harvard Business School Press, Cambridge (1999)

Poulsson, S.H.G., Kale, S.H.: The experience economy and commercial experiences. Mark. Rev. **4**(3), 267–277 (2004)

Relph, E.: Place and Placelessness. Pion, London (1976)

Rothschild, M.L.: Perspectives in involvement: current problems and future directions. Adv. Consum. Res. **11**, 216–217 (1984)

Rubinstein, R.L., Parmelee, P.A.: Attachment to place and the representation of the life course by the elderly. In: Altman, I., Low, S. (eds.) Place Attachment, pp. 139–163. Plenum, New York (1992)

Treem, J.W., Leonardi, P.M.: Social media use in organizations: exploring the affordances of visibility, editability, persistence, and association. In: Communication Yearbook, vol. 36, pp. 143–189 (2012)

Tuan, Y.F.: Space and Place: The Perspective of Experience. University of Minnesota, Minneapolis (1977)

Van Doorn, J., Lemon, K.N., Mittal, V., Nass, S., Pick, D., Pirner, P., Verhoef, P.C.: Customer engagement behavior: theoretical foundations and research directions. J. Serv. Res. **13**(3), 253–266 (2010)
Vargo, S.L., Lusch, R.F.: Service dominant logic: continuing the evolution. J. Acad. Mark. Sci. **36**(1), 1–10 (2008)
Wang, K.: Determinants of mobile value-added service continuance: the mediating role of service experience. Inf. Manag. **52**(3), 261–274 (2015)
Whittaker, S.: Theories and methods in mediated communication. In: The Handbook of Discourse Processes, pp. 243–286 (2003)
Wilson, J.H., Guinan, P.J., Parise, S., Weinberg, B.D.: What's your social media strategy? Harvard Bus. Rev. **89**(7/8), 23–25 (2011)
Zaichkowsky, J.L.: Measuring the involvement construct. J. Consum. Res. **12**(3), 341–352 (1985)

Factors Influencing Employees' Attitude Towards Personal Information Privacy

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Abstract. This study examines factors that influence an employee's attitude and decisions about the information privacy practices of corporations. Using a survey of 319 employees from different corporations, this study explores individual factors, organizational factors and environmental factors affecting attitude towards personal information privacy. The results show that prior privacy experience, trust in IT on functionality, trust in IT on predictability, trust in IT on helpfulness, policy enforcement, top management support and government regulation are key factors affecting employees' attitude towards personal information privacy. The results also show that employees' concern about personal information privacy is related to actual punishments for the invasion of privacy rather than oral warnings.

Keywords: Information security · Personal information privacy Invasion of privacy

1 Introduction

When personal information has become a valuable asset for personalized services or products, concerns about invasion of privacy related to consumers always exist (Lee et al. 2011). In 2016, IBM found that 60% of all IS (information system) attacks were carried out by insiders. Of these attacks, three-quarters involved malicious intent, and one-quarter involved inadvertent actors. Among these attacks, health care, manufacturing, and financial services are top three industries under attack (Zadelhoff 2016). The largest risk of privacy invasion exists within the company. The employees who deal with sensitive personal information of customers are those who are the most possible to cause privacy invasion. It also means that more than half of IS attacks could be avoided by regulating appropriate procedures of privacy protection or precautionary measures of privacy invasion.

In addition, studies show that more and more IT security breaches come from internal employees rather than external individuals (Rosenblatt 2015; Zadelhoff 2016).

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External individuals generally have to take the advantage of IS breaches to gain the control of IS and then steal the valuable personal information. Those acts require not only a lot of knowledge about IT security but also a lot of time to bypass the IS protection. Compared to external individuals, internal employees can access personal information easily. Internal employees can legally update, modify, delete, and search data stored in the company. It is harder to observe which employee or which activity is harmful to customers' information privacy. Employees are gatekeepers of customers' information privacy and executors of privacy regulations in companies.

The attitude of employees is the key to the success of privacy protection. When external individuals have to be proficient in IT skills to hack an IS, any internal employee can spread personal information easily. If employees with high privacy concern understand and recognize the importance of personal information, they will actively protect personal information. Bélanger and Crossler (2011) mention that most studies on information privacy discuss the explanation or prediction of behavioral intention of information privacy, but few studies focus on the formation of employees' attitude towards personal information privacy. Thus, the research objective of this study was to develop a research model for understanding employees' perception towards personal information privacy.

2 Literature Review and the Theoretical Framework

Personal information privacy has many definitions, but the main concepts are similar. Bélanger et al. (2002) focus on the control over the potential secondary uses of one's personal information. Secondary use refers to the practice that the collected data are used for purposes other than those originally collected. Smith et al. (1996) use collection, unauthorized secondary use, improper access, and errors to describe four dimensions of information privacy. Skinner et al. (2006) classify information privacy into individual, group, and organizational privacy. In this study, personal information privacy refers to one's ability to control information about oneself.

While existing studies have identified constructs and relationships, the majority of the studies did not provide an integrated view of the network of relevant constructs. Based on the empirical literature reviewed, three categories of variables that impact an employee's attitude towards personal information privacy were identified (Fig. 1). The first category relates to individual differences, the second category relates to organizational factors, and the third category relates to environmental factors. Although several pioneering studies have examined general privacy risks, few systematic attempts have been made to discuss the specific nature of privacy concerns among employees. Thus, these factors influence an employee's attitude towards the information privacy in the organization are discussed in the following sections.

2.1 Individual Factors

Past experiences of privacy, trust in IT on functionality, predictability and helpfulness are four variables included in individual differences. Privacy issues from past experiences are critically important because vendors may access a large volume of personal

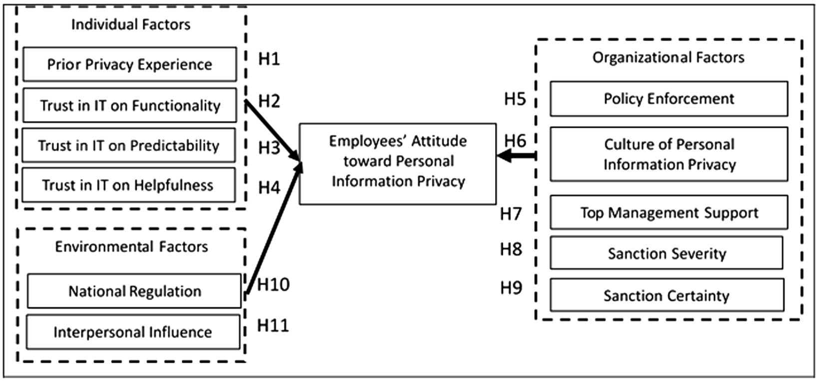

Fig. 1. Research model

information. Past victims of personal information abuse have a higher degree of concern about information privacy than they used to be (Xu et al. 2012). Thus, more prior privacy experience will have a positive impact on the protection of personal data. Thatcher et al. (2011) pointed out that employees' trust in IT will affect their attitude of IT use. Individual's trust in IT comes from functionality, predictability, and helpfulness. Individual will trust IT with more functionality, predictability, and helpfulness (Thatcher et al. 2011). When employees have high trust in IT, they will have positive attitude towards personal information privacy.

Therefore, this study proposed:

H1: Employees with more prior privacy experience will have positive attitude towards personal information privacy.

H2: Employees with high trust in IT on functionality will have positive attitude towards personal information privacy.

H3: Employees with high trust in IT on predictability will have positive attitude towards personal information privacy.

H4: Employees with high trust in IT on helpfulness will have positive attitude towards personal information privacy.

2.2 Organizational Factors

Policy enforcement, culture of personal information privacy, top management support, sanction severity, and sanction certainty are five variables related to organizational factors. Their effects on attitude towards personal information privacy are discussed as follows. Employees' awareness of organizational IT security issues have positive effects on the compliance with information security policy in an organization (Bulgurcu et al. 2010). The result also applies to information privacy. Employees with high organizational attitude towards personal information privacy will have positive attitude towards personal information privacy. When organizations implement information security policy, employees' understanding about information security will increase (Kemp and Kemp 2005; Knapp et al. 2006). As organizations adopt the policy of personal information privacy and let employees know related regulations, employees will have more positive attitude towards personal information privacy. Organizational culture will affect employees' beliefs, and the culture of personal information privacy affects employees' beliefs as well (Knapp et al. 2006). The commands and considerations of top management is always put in the first priority by employees (Knapp et al. 2006). If top management is interested in information privacy issues, the priority of information privacy will be higher. When top management support of personal information privacy is high, the attitude towards personal information privacy will also be high.

Sanctions are usually used as a mean to threaten potential offenders. A low level of sanction certainty has been identified as an important reason for increased frequency of employee theft (Lau et al. 2003). Employees want to know more about personal information privacy to avoid being punishment if sanction is certain. In addition, a certain level of sanction severity is a necessary deterrent to ensure compliance with information privacy (Li et al. 2014). A high level of perceived sanction severity has been found to reduce the misuse of IS resources, such as personal information (Li et al. 2014). Therefore, sanction severity and sanction certainty will positively affect the attitude towards personal information privacy.

Therefore, this study proposed:

H5: Employees with positive perception of policy enforcement will have positive attitude towards personal information privacy.

H6: Employees with positive culture of personal information privacy will have positive attitude towards personal information privacy.

H7: Employees with high top management support will have positive attitude towards personal information privacy.

H8: Employees with high sanction severity will have positive attitude towards personal information privacy.

H9: Employees with high sanction certainty will have positive attitude towards personal information privacy.

2.3 Environmental Factors

Government regulation and interpersonal influence are two variables included in environmental factors. As government enacts relevant regulations on personal information privacy to effectively curb the illegal use of personal information, employees' attitude towards personal information privacy will be more positive (Chang et al. 2006). Interpersonal influence is exerted by a peer group in encouraging a person to change his/her attitudes and values in order to conform to group norms (Korir and Kipkemboi 2014; Taylor and Todd 1995).

Therefore, this study proposed:

H10: Strict government regulation will positively affect employees' attitude towards personal information privacy.

H11: Interpersonal influence will positively affect employees' attitude towards personal information privacy.

3 Methodology

3.1 Measurement

The purpose of our study was to understand employees' attitude towards information privacy and identify the factors that influence employees' attention towards information privacy. These factors include individual differences, organizational factors, and environmental factors. All scales were revised from past studies. These scales were translated to Chinese and pretested with four professors and three doctoral students. The Chinese questionnaires were revised according to the suggestions and discussions with professors and doctoral students. Then, 27 employees were invited to do the pilot test. Employees' responses to the recruiting process of participants were used to refine the survey of this study. In addition, these employees were asked to check if descriptions of survey items could be understood easily. Both the suggestions of pretest and pilot test were adopted and used in the following survey.

3.2 Survey Design

Researchers invited alumni who worked in Manufacturing Industry, Service Industry and Financial Industry to participate in the survey through University Alumni Association and the Alumni Association of Department of Information Management. At the end of this study, employees from 22 companies responded the invitation. The paper questionnaires were mailed to each company. Each questionnaire contained the web address of online survey and some background information about this study without disclosing too many details. Each participant could fulfill the paper questionnaire and send it back to the researcher or just fulfill the questionnaire online. Since participation of the study was completely voluntary, some respondents submitted empty or only partially filled questionnaires. Those incomplete questionnaires were subsequently eliminated. In the end 319 responses were usable.

4 Data Analysis and Results

The reliability and validity of the measurement were analyzed. Reliability test showed that the Cronbach's α of all constructs are higher than 0.7, except the Prior Privacy Experience (Cronbach's $\alpha = 0.68$). Validity test was assessed by content validity and construct validity. The responses of pretest and pilot test showed that the questionnaire achieved content validity. Principle component analysis was used to assess the construct validity. The results showed that all factor loadings of each item was larger than 0.35. Thus, the data had robust construct validity.

Multiple regression analysis was used for assessing the hypotheses. Four assumptions of multiple regression, including normality, multicollinearity, homoscedasticity, independence of the error terms, were examined before assessing the hypotheses. The results showed that the data satisfied four assumptions of multiple regression.

The background of participants showed that 53% of the responses were women. The largest group of responses were individuals between 30 and 39 years old.

Participants' top three occupations were Medical Industry (26%), Manufacturing Industry (24%) and Financial Industry (23%). The results of multiple regression analysis were shown in Table 1. Thus, H1, H2, H3, H4, H5, H7, and H10 were supported.

Table 1. Results of regression analysis

Variables	Beta coefficient	Variables	Beta coefficient
Prior privacy experience	0.196***	Policy enforcement	0.150**
Trust in IT on functionality	0.118**	Culture of personal information privacy	0.095
Trust in IT on predictability	0.088*	Top management support	0.225***
Trust in IT on helpfulness	0.094*	Sanction severity	–0.009
Government regulation	0.088*	Sanction certainty	0.022
Interpersonal influence	–0.001		

***: $p < 0.001$, **: $p < 0.05$, *: $p < 0.1$, R-squared = 0.367

5 Discussion

The enterprise usually owns a large volume of personal information during the contact with customers. As more and more transactions take place online, the collection of personal data is easier than before. The enterprise could combine personal data with other online data to understand customers' purchasing processes. Reasonable use of personal data will be able to bring the enterprise a large amount of benefits. As the result, avoiding the abuse of personal data becomes an important issue.

If the regulation or attitude to protect personal data is incomplete, it increases the possibility that a company could trade personal information for money with other companies. Thus, the announcement of Personal Information Privacy Act in Taiwan responds to the requirements to regulate possible abuse of personal data.

However, the employees are the gatekeepers of personal information of an organization. Their attitudes towards personal information protection will directly lead to increase or decrease the intrusion of personal information. Thus, this study aims to explore factors affecting employees' attitude towards personal information privacy. The results are discussed as follows.

5.1 Individual Differences

When employees use organizational IT to complete their jobs, their trust to the organization IT on functionality, predictability, and helpfulness positively affects their attitudes towards personal information privacy. It indicates that the protection of personal information is closely related to the capability of organization IT. It is not easy to protect customers' personal information without the support of IT. Sufficient IT supports in the organization may also provide useful and easy function to protect personal information.

Prior experiences of privacy positively increase the attitude towards personal information privacy. People who have personal experiences of invasion of privacy may suffer financial losses or damage to personal or real property. These experiences along with other privacy invasion news which are disclosed in public media can form employees' beliefs about privacy. The more knowledge and experiences employees have about privacy, the more emphasis they will put on privacy.

5.2 Organizational Factors

The results show that policy enforcement and top management support significantly affect the attitude towards personal information privacy. When the organization policy educates employees about organizational regulations of personal information privacy, employees will pay more attention to these regulations. Warnings and possible punishments about violating information privacy makes employees consciously explore news of information privacy. This then leads employees to have a positive attitude towards personal information privacy. The influences of top management is similar to policy enforcement. The attitude and behavior of top management is frequently discussed and observed by employees. Thus, the top management support can increase employees' attitude towards personal information privacy.

Nevertheless, culture of personal information privacy, sanction severity and sanction certainty do not significantly affect the attitude towards personal information privacy. One reason may be that employees consider that other employees do not attach great importance to personal information privacy. In addition, organizations may not be able to develop complete punishments for the invasion of information privacy. The methods of invading personal information privacy are evolving with the development of IT. It is hard to develop complete sanctions for all kinds of invasion of personal information. Thus, only when organizations and the top management educate employees the importance of personal information privacy, employees will change their attitude towards personal information privacy.

5.3 Environmental Factors

For employees, the influences of government regulation are noticeable. The information protection regulations announced by the government are published and discussed over the public media. As employees are aware of these discussions, they will be cautious about the invasion of personal information privacy and affect their attitude towards personal information privacy.

Advices from friends are usually persuasive for an individual. Nevertheless, this study shows that the persuasion of these advices diminishes in the organization. Employees generally do not adopt their friends' advices directly because employees have to consider their companies' culture and their leaders' management style. Their friends are not in the employees' companies, so they may not fully understand employees' struggles in organizations. This may be one reason why the influences of friends on employees' attitude towards personal information privacy is not significant.

6 Conclusions

Privacy issues become critically important as merchants and vendors may access a large volume of potentially sensitive personal information. For employees of merchants and vendors, they are gatekeepers for personal information. Their attitude towards personal information privacy will directly lead to the success or failure of personal information privacy protection. Thus, this study explores factors affecting employees' attitude towards personal information privacy. For practitioners, the results of this study show that managers could remind employees of the importance of personal information privacy through actual punishments and government regulations. Employees will take information privacy seriously when they see actual cases of punishments. For researchers, this study proves that the change of attitude for personal information privacy is not easy. Factors related to the immediate change of behavior are critical to formulate the attitude of information privacy protection.

References

Bélanger, F., Crossler, R.E.: Privacy in the digital age: a review of information privacy research in information systems. MIS Q. **35**(4), 1017–A36 (2011)

Belanger, F., Hiller, J.S., Smith, W.J.: Trustworthiness in electronic commerce: the role of privacy, security, and site attributes. J. Strateg. Inf. Syst. **11**(3–4), 245–270 (2002). https://doi.org/10.1016/s0963-8687(02)00018-5

Bulgurcu, B., Cavusoglu, H., Benbasat, I.: Information security policy compliance: an empirical study of rationality-based beliefs and information security awareness. MIS Q. **34**(3), 523–A7 (2010)

Chang, I.-C., Hwang, H.-G., Yen, D.C., Huang, H.-Y.: An empirical study of the factors affecting Internet security for the financial industry in Taiwan. Telematics Inform. **23**(4), 343–364 (2006). https://doi.org/10.1016/j.tele.2005.11.001

Kemp, M., Kemp, M.: Beyond trust: security policies and defence-in-depth. Netw. Secur. **2005** (8), 14–16 (2005). https://doi.org/10.1016/s1353-4858(05)70271-3

Knapp, K.J., Marshall, T.E., Kelly Rainer, R., Nelson Ford, F.: Information security: management's effect on culture and policy. Inf. Manage. Comput. Secur. **14**(1), 24–36 (2006). https://doi.org/10.1108/09685220610648355

Korir, D.K., Kipkemboi, F.: The impact of school environment and peer influences on students' academic performance in Vihiga County, Kenya. J. Educ. Pract. **5**(11), 1–11 (2014)

Lau, V.C.S., Wing Tung, A., Ho, J.M.C.: A qualitative and quantitative review of antecedents of counterproductive behavior in organizations. J. Bus. Psychol. **18**(1), 73–99 (2003)

Lee, D.-J., Ahn, J.-H., Bang, Y.: Managing consumer privacy concerns in personalization: a strategic analysis of privacy protection. MIS Q. **35**(2), 423–A8 (2011)

Li, H., Sarathy, R., Zhang, J., Luo, X.: Exploring the effects of organizational justice, personal ethics and sanction on internet use policy compliance. Inf. Syst. J. **24**(6), 479–502 (2014). https://doi.org/10.1111/isj.12037

Rosenblatt, S.: The biggest cyberthreat to companies could come from the inside. In: CNET, 8 January (2015). https://www.cnet.com/news/the-biggest-cyber-threat-to-companies-could-come-from-the-inside/. Accessed 5 Feb 2017

Skinner, G., Han, S., Chang, E.: Defining and protecting meta privacy: a new conceptual framework within information privacy. In: 22nd International Conference on Data Engineering Workshops (ICDEW 2006), Presented at the 22nd International Conference on Data Engineering Workshops (ICDEW 2006), pp. 101–101 (2006). https://doi.org/10.1109/icdew.2006.46

Smith, H.J., Milberg, S.J., Burke, S.J.: Information privacy: measuring individuals' concerns about organizational practices. MIS Q. **20**(2), 167–196 (1996)

Taylor, S., Todd, P.A.: Understanding information technology usage: a test of competing models. Inf. Syst. Res. **6**(2), 144–176 (1995)

Thatcher, J.B., McKnight, D.H., Baker, E.W., Arsal, R.E., Roberts, N.H.: The role of trust in postadoption IT exploration: an empirical examination of knowledge management systems. IEEE Trans. Eng. Manage. **58**(1), 56–70 (2011). https://doi.org/10.1109/tem.2009.2028320

Xu, H., Gupta, S., Rosson, M.B., Carroll, J.M.: Measuring mobile users' concerns for information privacy. In: ResearchGate, Presented at the 33th ICIS, Orlando, January, pp. 1–16 (2012). https://www.researchgate.net/publication/290022632_Measuring_mobile_users'_concerns_for_information_privacy

Van Zadelhoff, M.: The biggest cybersecurity threats are inside your company. In: Harvard Business Review, 19 September 2016. https://hbr.org/2016/09/the-biggest-cybersecurity-threats-are-inside-your-company. Accessed 5 February 2017)

How Does the Review Tag Function Benefit Highly-Rated Popular Products in Online Markets?

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Abstract. Since online reviews have become an increasingly important information source for consumers to evaluate products during online shopping, many platforms started to adopt review mechanisms to maximize the value of such massive reviews. In recent years, the review tag function has been adopted in practices and leading the research of sentiment and opinion extraction techniques. However, the examination of its impact has been largely overlooked. In this paper, we specifically look into the effect of the tag function on the evaluation of highly-rated popular products and helpfulness perception of their reviews by proposing a framework through the lens of attribution theory. Experimental methods were utilized to test our hypotheses. Our findings demonstrate the importance of tag function application as it further increases consumers' product evaluation for popular products. We also found that different tag function appearances influence consumers' cognitive biases in review helpfulness perception.

Keywords: Online reviews · Review tag · Product evaluation
Perceived bias

1 Introduction

User-generated product reviews are very popular and widely adopted in online markets. Because of their great value in reducing information asymmetry of the Internet, online reviews are considered as a facilitating tool for consumers to make purchase decision [1–3]. Hence, the impact of online reviews is increasingly important and has been intensively investigated by researchers [4–6].

Many research focuses on the role of product's average review ratings, as it serves as a salient signal for potential consumers to learn about the product [7]. Prior research have found the impact of product ratings on consumers' perceptual and behavioral outcomes in the shopping process, such as product evaluation, sales, consumer revisit intention, and perception of product review information [4, 6, 8, 9].

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However, for consumers, the mere average rating information might not suffice. The plenty of information embedded in review content is also important in providing consumers with different opinions on the product [10]. To assist consumers in reading the massive review content, market platforms introduce new mechanisms to help them identify the most important or valuable information [1, 11].

The automatic review tagging system is one of such attempts. The automatic tagging system utilizes and extracts the content of consumer-generated reviews to generate automatically products' feature-related tags using text-mining technologies. In current practices, both TripAdvisor.com and Tmall.com have been presenting the most frequently mentioned review content on top of all the reviews. While TripAdvisor only shows the tag label (shown in Fig. 1), i.e., the most frequent features that people comment on, Tmall displays the tag labels, the corresponding sentiment as well as the number of mentions using different colors (shown in Fig. 2).

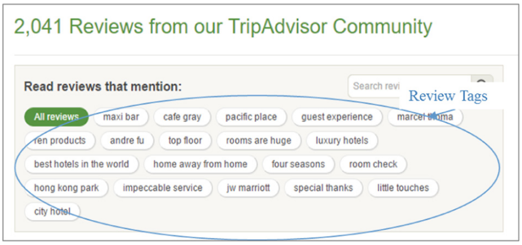

Fig. 1. Review tag function on TripAdvisor.com

Fig. 2. Review Tag function on Tmall.com

Thus, besides an average rating, the tags derived from review content also facilitate consumers to instantly grasp the keywords, or collective opinions from prior consumers. However, as most prior research has focused on examining the impact of review rating on consumers' product evaluation or information perception [6, 7, 12], little is known about how the review tag function would matter.

To understand the role of the review tag function, an intuitive starting point is to learn how the function is applied. The review tag function is mostly used for popular products [13] because of two reasons. First, only sufficient texts could afford a basis for extracting tags. For an unpopular product, its number of reviews could be too small to produce tags. Second, reviews for hot-pick products are often too numerous to be processed by humans in an effective way. For such products, the tag function could also bring the most benefits for their potential consumers.

Our research questions rise naturally from the above discussions. From a practical aspect, for a highly-rated popular product, its high rating might have already brought a positive impact on consumers' perception towards the product and its reviews. It would be beneficial for managers or sellers to understand how the review tag function would influence their potential consumers in evaluating the product. In particular, in this study, we aim at answering the following two questions. First, will the tag function influence consumers' evaluation towards highly-rated popular products? Second, will the presented tags influence consumers' perception towards product reviews?

To answer the questions, we tested our hypotheses by utilizing online experiments using mock product webpages. By assigning respondents to conditions of different tag function settings, we collected data on their responses of product evaluation and review perception. Our findings revealed that, tag function adoption increase the consumers' evaluation towards a product. Meanwhile, we found that people would prefer negative reviews for a popular product when all its tags appear positive, while people's preference for positive reviews does not change by the adoption of tag function.

The remaining part of the paper is arranged as follow. We first introduce the current usage of the review tag function based on data collected from Tmall.com, and present our theory background. After we propose our hypotheses on the impact of the review tag function, we present our experiment process as well as the results. In the last section, we discuss the contributions and limitations of the research.

2 Research Background

2.1 Review Tag Function

Archak, Ghose [10] described a simple version of a tag-generating tool. The tag-generation process includes and is not limited to feature extraction, sentiment classification and text summarization based on reviews [13]. As a result, a set of noun phrases and the respective sentiment are produced, which corresponds to product features and their evaluation.

Tag function could be presented with different appearances. We take the current tag function on Tmall.com as our target prototype. Emerged from Taobao.com, Tmall.com focuses on B2C transactions and provides higher quality and compliances. Current practice in Tmall.com limits the total number of review tags to ten, so that the function at most displays the top ten features and their sentiment according to the feature frequency ranking. On Tmall.com, the positive tags are presented in red color and negative tags are in green color. Both types of tags display the frequency of the features being mentioned in reviews. And normally on Tmall.com, if there are negative tags, they are often placed after all other positive tags, being less noticeable.

To obtain a direct understanding of the review tag function for popular products on Tmall.com, we selected products from different categories and give an overview of the tag function usage on Tmall.com. We used the name of each product category as keyword and randomly selected ten products for each keyword from the top 100 most-sold items in the search results. We collected their price, sales, promotion, tag function usage information and review information from their pages.

In total, we collected information for 340 popular products, and around 67% (228 out of 340) of them were using the tag function. Table 1 shows the descriptive statistics of the collected data. For those using the tag function, the average number of tags is 9.57. The average numbers of positive and negative tags are 8.12 and 1.45 respectively, which partially supported that negative reviews are much fewer than positive ones [3, 14].

Table 1. Descriptive statistics of review tag function usage on Tmall.com

N = 340	Subsample 1: with tag function					Subsample 2: without tag function				
Product features	N	Mean	Std. dev.	Min	Max	N	Mean	Std. dev.	Min	Max
price	228	223.52	618.17	0.43	5,299	112	376.27	789.18	1	3,999
sales	228	16,953.61	23,516.47	17	160,436	112	13,301.85	25,433.46	1	115,150
# of reviews	228	51,860.64	84,039.34	61	480,625	112	39,075.18	78,821.53	0	410,389
average rating	228	4.81	0.08	4.40	5	112	4.60	1.01	0	5
# of tags	228	9.57	1.85	2	10	112	n/a	n/a	n/a	n/a
# of positive tags	228	8.12	1.65	2	10	112	n/a	n/a	n/a	n/a
# of negative tags	228	1.45	0.93	0	4	112	n/a	n/a	n/a	n/a

As shown, some of the features showed differences between the two subsamples, with tag function and without tag function. We performed t-tests and found that the average review rating in Subsample 1 is significantly higher than the rating in Subsample 2 ($M = 4.812$ vs 4.598, $t\ (338) = 3.19$, $p = 0.0015$). Also, the average ratings for Subsample 1 products are above 4.4, indicating that products using the tag function are highly rated.

In Subsample 1, price is marginally lower than the price in Subsample 2 ($M = 223.522$ vs 376.267, $t\ (338) = 1.95$, $p = 0.052$). The sales and the number of reviews did not show significant differences across the two subsamples.

With the above being shown, we identify a typical appearance of the review tag function for popular products on Tmall.com. The typical appearance consists of nine or ten tags, including one or two negative tags and eight or nine positive tags.

For popular products, an all-positive appearance of the review tag function provides a strong support to the product from prior buyers, which intuitively could be an ideal situation for sellers to promote their products. Therefore, besides a typical review tag appearance, we are also interested in the all-positive appearance, so that to understand their difference in affecting consumers' perceptions towards the product as well as its reviews.

2.2 Attribution Theory

Attribution theory was developed in the field of social psychology for understanding how people perceive and evaluate the behaviors of others [15]. Attribution refers to the perception or the inference of cause. Attribution research is concerned with all aspects of causal inferences.

There are three assumptions in the theory [16]. The first one is that people interpret behavior in terms of its causes and that these interpretations play an important role in determining reactions to the behavior [15, 17]. The second assumption is that people are generally motivated to gain a realistic understanding of the causes that have led to different events in their personal domain [15]. Third, it is assumed that a causal understanding serves the function of attaining personal goals and survival [18].

At first, when Heider proposed the attribution theory in his book [15], he distinguished causes of actions into two basic types, personal or internal causes, and situational or external causes. For example, if Tom recommends a movie to others, his action might be due to his internal taste for this movie, or to other external factors, e.g. every audience of the movie on that day is given a voucher.

Later, Kelley extended and elaborated on how individuals infer causes [19, 20]. According to his topology of person–stimulus–circumstances, general attributions could be made to the person (Tom's taste for the movie), the stimulus (the movie quality), and circumstances (special gifts for the audiences).

Information is used to facilitate an observer's attribution of a behavior. One important piece of information is consensus information. Kelley [20] proposed that when people make attribution to an actor's behavior, they would take into consideration how others behave in the same situation. The term, consensus information, is used to refer to the way in which other people respond to the stimulus. Take Tom's recommending the movie as an example. If everyone who has watched the movie recommends it, we would observe high consensus. In the meantime, when most others behave in a similar way to Tom, i.e., there is high consensus, we, as observers, tend to attribute to product-related causes, which are external to Tom. But as consensus decreases, our attribution would be more internal to him [21].

The impact of consensus varies with a number of mediating factors, such as the salience of the consensus, representativeness of the sample, relevance of the consensus and so on [22]. Among them, sample representativeness seems to be of greater importance. As noted in Kassin [22], one of the most severe limitations of consensus is that, the consensus is based on the observation of a limited sample. The consensus utilization requires observers' beliefs in the sample representativeness [23], otherwise, the validity of consensus would be violated.

The theoretical development of attribution theory had enabled consumer research to explore a variety of studies, specifically the research line which examines the process by which individuals assign causal agency to outcomes experienced by others [24].

3 Hypotheses Development

Our context of online reviews readily fits into the principle proposed by Kelley. When making a purchase decision, individuals would observe others' product experience expressed in reviews. When processing the review information, they would attribute the review content to either product-related features or reviewers' characteristics.

There have been studies using attribution theory within the context. For example, Chen and Lurie [25] studied the effect of temporary contiguity on reviews' causal attribution. They found that when reviews' writing closely follows consumption, positive reviews would be more attributed to products and hence be more valued. In examining the review dispersion, He and Bond [24] found that consumers taste similarity moderates the relationship between review dispersion and the attribution to reviewers.

In online markets, potential consumers obtain consensus on product evaluation from two sources, the overall rating and the summarized review tags. The overall rating represents the average numeric evaluation towards the product, reflecting a simple holistic assessment of the product. As for review tags, each of the tags represents a set of product-related features and the respective sentiment, either positive or negative. Since review tags demonstrate the evaluation of the most frequent features, they can also be regarded as high consensus information.

According to the attribution theory, the consensus information affords a basis for confidence in one's judgment [20]. If a product has a high rating, potential consumers tend to attribute the consensus to product-related causes, prevailing confidence in a positive product evaluation.

Similarly, if a popular product is shown with all-positive tags or typical tag appearance, the dominant positive consensus would be further strengthened, yielding a higher evaluation towards the product comparing to the situation when only overall rating is shown. Therefore, we hypothesize the following.

Hypothesis 1. When the highly-rated popular product is shown with all-positive tags or typical tag appearance, consumers' product evaluation is more likely to be higher comparing to when there is no tag function.

Other than affecting product evaluation, the presence of the review tag function could also influence consumers' utilizing review information.

For review systems without tag function, consensus comes from the overall rating information. Suppose a popular product is highly-rated, its high overall rating could result in consumers' tendency of favoring positive reviews, as positive reviews are more likely to be attributed to product-related causes. On the other hand, a consumer might tend to attribute negative reviews to reviewer-attributed causes, and perceive them as less helpful in reflecting the product's true evaluation. Therefore, a positive bias could be yielded.

For review system with tag function, besides a high rating, if all tags for a product are positive, consumers' preference for positive reviews would be further strengthened due to the more salient positive consensus. But in terms of the negative reviews, since negative evaluation is not included in consensus information, consumers tend to regard negative reviews as attributable to reviewers and perceive them as less helpful. So, we hypothesize the following.

Hypothesis 2a. When a highly-rated popular product is shown with all positive tags, consumers are more likely to perceive positive reviews as helpful comparing to when there is no tag function.

Hypothesis 2b. When a highly-rated popular product is shown with all positive tags, consumers are less likely to perceive negative reviews as helpful comparing to when there is no tag function.

However, different from all-positive tag appearance, a typical tag appearance might draw consumers' attention to the negative tag and lessen their confidence in the high product evaluation. Therefore, the preference for positive reviews would be reduced, but the preference for negative reviews prevail due to its value in reflecting product-related information. We hypothesize the following.

Hypothesis 3a. When a highly-rated popular product is shown with typical tag appearance, consumers are less likely to perceive positive reviews as helpful comparing to when there is no tag function.

Hypothesis 3b. When a highly-rated popular product is shown with typical tag appearance, consumers are more likely to perceive negative reviews as helpful comparing to when there is no tag function.

However, the above discussion neglects the role of the consensus' perceived validity [23]. As shown in Sect. 2.1, a typical appearance of tag function contains not only positive, but also negative tags. When a product is shown with only positive tags, potential consumers would assume the consensus sample to be positively biased. In such cases, the effect of high positive consensus might perish. Consumers might be willing to obtain negative opinions of the product, so as to acquire more non-biased views derived from product-related reflection. Therefore, a negativity bias in reviews could emerge for popular products with all-positive tag function appearance. So, contradicting Hypothesis 2b, we also hypothesize the following.

Hypothesis 4. When a highly-rated popular product is shown with all positive tags, consumers are more likely to perceive negative reviews as helpful comparing to when there is no tag function.

4 Methodology

We first utilized an online experiment in order to test our hypotheses on the review tag function. We manipulated the tag function appearances with a between-subjects design.

4.1 Manipulation

We selected a computer product as our manipulation target for the experiment. Computer is a common product among students. As we would use student sample to conduct our survey, we expected the selected product to be a possible choice considered by the sample group.

A computer product with the tag function from Tmall.com was selected as our prototype to create our mock pages for manipulation. The experimental manipulation used in the study was developed according to the above overview of the randomly collected products in Table 1. To test our hypotheses, we used two appearances of the tag function. The first one, the appearance with ten positive tags (we call it 10PT and thereafter), and the second one, the typical appearance with nine positive tags and one negative tag (we call it 9PT1NT). Also, as a control, we create an extra group with no tag function shown in the webpages.

For each group, we kept every element the same except for the tag appearances. The product descriptions were copied from the prototype's webpage, while eliminating irrelevant information such as recommended products offered by the seller.

In terms of the product reviews, we first decided the number of reviews we would use for the mock page. Since normally, people would not read all the reviews for a popular product. As each page of reviews contains only 20 pieces of reviews, consumers would not try to click through all the pages to obtain information. We arbitrarily decided to collect around 200 reviews from the prototype webpage, which would induce at least nine or ten times of clicks to finish reading all the reviews.

Tag function had been used in our prototype webpage. It contained ten positive tag labels. For each tag in the prototype webpage, we collected the proportional number of reviews. So, in our mock webpage, the frequency of each review tag showed the number of reviews collected from the corresponding review tag.

Besides the reviews from all the positive tags, we created a negative tag. To avoid bias for any specific product feature, the negative tag was made with a general label on purpose. After considering the normality of review tag frequency distribution and comparing the current frequencies of positive tags, we set the frequency of the only negative tag as the same as the second lowest frequency of positive tags collected above. And the reviews for the negative tags were selected manually. Two coders independently judged whether the selected reviews matched with the negative tag and their evaluations were consistent.

Therefore, 210 reviews for a total of eleven tags were prepared. They were all displayed in each of the three groups. But in 10PT group, only ten positive tags were shown in the tag function area, while in 9PT1NT, nine positive tags and a negative tag were shown.

4.2 Stimulus Preparation

In preparation of the stimuli for our experiment, we needed to identify the sentiment of the text reviews. First, we randomly selected 60 reviews from the prototype's Tmall webpage, with the intention of selecting five from them as our stimulus reviews.

To assess the sentiment of the reviews, we recruit two coders to evaluate the sentiment of the reviews. The coders were unaware of the study's purpose. Each coder was presented review texts and were asked to rate whether the review is positive, negative or neutral. To prevent potential biases, we did not present any description of the computer product. Second, to prevent ordering bias, each coder received a different random order of reviews. We also made sure the two coders complete the tasks independently.

For the reliability of the coded review sentiment, two reliability scores were calculated for each of the product reviews [26]. We obtained 0.8208 on Krippendorff's alpha, which exceeded the recommended value 0.70 [27]. We also had 96.67% on Cohen's kappa which also exceeded the recommendation value of 0.80 [28].

As the sentiment coding is deemed reliable, we dropped the two reviews with coders' disagreed evaluation, and grouped the remaining ones by their sentiment. Then we randomly selected two from positive reviews, one from neutral reviews and two from negative reviews as our stimulus.

4.3 Experiment Procedure

Participants were recruited from an IS course at a Chinese university. Participants received extra credit for their participation, and they were randomly assigned to three experimental conditions.

First, after giving their consent, participants were instructed to read the product information from a webpage of Tmall.com for at least three minutes. All participants were able to read Chinese to participate in the survey. They were free to browse all the descriptions or reviews, or to read selected reviews by clicking each review tag of the product. Next, we used an attention test to ensure whether participants did read the product information.

After that, participants received the survey questions, followed by demographic items. They were first asked to state their overall evaluation of the product. Next, positing randomly in the sequence, five stimulus reviews are presented to participants, one at a time. By reading each review, participants were asked to report their perceptions of the review helpfulness. The helpfulness perception was measured by using three items adapted from Sen and Lerman [29] and Yin, Bond [30] All items are of 9-point semantic differential-scale, as presented in Table 2. Also, to understand the participants' causal attribution, we asked an additional question measured by a 9-point semantic differential scale: "To what extent are the contents of the consumer review based on the product?"

Table 2. Measurement items

Variable		Items
Product evaluation	PE1	How do you think of the product reviewed? [Very good/Very bad]
	PE2	How do you think of the product reviewed? [Very desirable/Not at all desirable]
Helpfulness perception	HP1	How do you think of the review? [Very useful/Not at all useful]
	HP2	How do you think of the review? [Very accurate/Not at all accurate]
	HP3	Assuming that you were thinking of buying this product, how likely would you be to use the above consumer review in your decision-making? [Very likely/Very unlikely]

Note: The measurements are developed based on the prior work of Sen and Lerman [29] and Yin, Bond [30]. All items are of 9-point semantic differential-scale.

Also, to understand the participants' causal attribution, we asked an additional question measured by a 9-point semantic differential scale: "To what extent are the contents of the consumer review based on the product?"

5 Results

In total, 101 participants completed the experiment. Before we conducted further analyses, we dropped four responses that failed to answer correctly in the attention test. We also dropped five responses for that their response duration was less than three minutes. After removing all the invalid responses, we had a total of 92 complete responses. Demographics of the participants are shown in the Table 3.

Table 3. Demographics

Participants	Items	Percentage	Participants	Items	Percentage
Gender	Male	63.04%	Age	19–20	21.74%
	Female	36.96%		21–22	65.22%
				23–24	13.04%
Monthly expense	Less than 500 rmb	1.09%	Years of using Taobao.com	Less than 1 year	1.09%
	500–999 rmb	25.00%		Around 3 years	45.65%
	1000–1499 rmb	53.26%		Around 4 years	27.17%
	1500–1999 rmb	11.96%		Around 5 years	13.04%
	2000–2499 rmb	4.35%		Around 6 years	6.52%
	2500–2999 rmb	1.09%		Around 7 years	4.35%
	3000 rmb or more	3.26%		Around 8 years	1.09%
				10 years or more	1.09%

Table 4 shows the descriptive statistics and correlation matrix of constructs.

5.1 Measurement Reliability and Validity

For exploratory factor analysis, we used principal components analysis with both varimax and oblimin rotations [31]. The result consistently provided two factors. All our items loaded as expected on their focal factors and loaded less than 0.4 on the other factor. Therefore, we retained all indicators.

Next, we conducted confirmatory factor analysis to examine the reliability and validity of the two constructs in the study. Cronbach's alpha for product evaluation was

Table 4. Descriptive statistics and correlation matrices

	Mean (Std.Dev)	PE	PE1	PE2	HP	HP1	HP2	HP3
PE	6.57 (1.32)	1						
PE1	6.88 (1.41)	0.88	1					
PE2	6.25 (1.56)	0.90	0.58	1				
HP	4.97 (2.30)	0.14	0.13	0.12	1			
HP1	5.33 (2.50)	0.15	0.14	0.13	0.94	1		
HP2	4.69 (2.28)	0.15	0.13	0.13	0.94	0.83	1	
HP3	4.88 (2.56)	0.10	0.11	0.06	0.94	0.83	0.83	1

0.734 and that for perceived helpfulness was 0.935. Also, the composite rho values for the two constructs were 0.882 and 0.958 respectively, indicating sufficient internal consistency and reliability [32, 33]. To establish convergent validity, we tested the average variances extracted (AVEs) for the two constructs, yielding 0.789 and 0.885, which were well above 0.5 and demonstrated convergent validity [33]. Finally, the data also passed the Fornell and Larcker's test, indicating discriminant validity [34].

5.2 Hypotheses Testing

Our first hypothesis is whether product evaluation varies between with- and without-tag-function groups. A t-test was performed to examine the difference in product evaluations across different conditions.

In line with our hypotheses, the result showed that the difference in product evaluation between with-tag-function group and control group was significant ($M = 6.775$ vs 6.172, $t(90) = 2.12$, $p = 0.037$). Evaluation to product shown with tag function is significantly higher than the evaluation to product shown without tag function, despite that all the other information is the same in both conditions.

Next, we inspected the three groups with more details. We did separate t-tests to examine the two with-tag-function groups comparing to the control group. For the 10PT group, we found that the product evaluation is higher than the evaluation in control group with marginal significance ($M = 6.722$ vs 6.172, $t(57) = 1.545$, $p = 0.064$). In the 9PT1NT group, the product evaluation is significantly higher than that in control group ($M = 6.818$ vs 6.172, $t(63) = 1.997$, $p = 0.025$). Figure 3 shows the difference in product evaluation at with 95% confidence intervals.

Therefore, we conclude that our Hypothesis 1 is supported. When product is shown with the two types of tag function, it is evaluated higher comparing with when it is shown without tag function.

To test our hypotheses on tag function's impact on reviews, we converted our data into review level. First of all, we tested whether the positivity bias or negativity bias exist. We performed an ANOVA test to investigate the difference in perception level across positive, neutral and negative sentiment. The results confirmed that both two biases exist ($M_{positive} = 4.780$ vs $M_{neutral} = 2.554$ vs $M_{negative} = 6.350$, $F(2, 457) = 132.43$, $p < 0.001$). Reviews' helpfulness perception increases when reviews are either

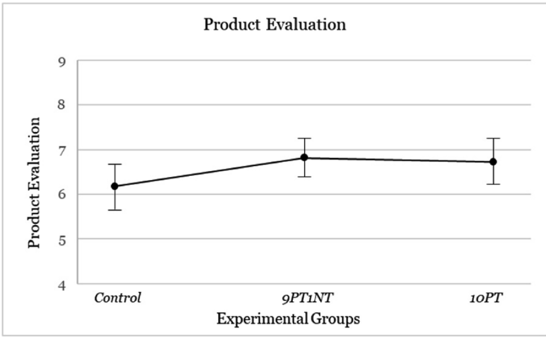

Fig. 3. Product evaluation

positive or negative comparing to when reviews are neutral. Figure 4 shows the differences at with 95% confidence intervals.

The responses to our supplementary question on participants' causal attribution also supported our assumption that the more the reviews are attributed to product features, the more they are perceived as helpful. Review helpfulness and the causal attribution were highly correlated and an additional ANOVA test reported significant and consistent increases in helpfulness perception across different attribution level.

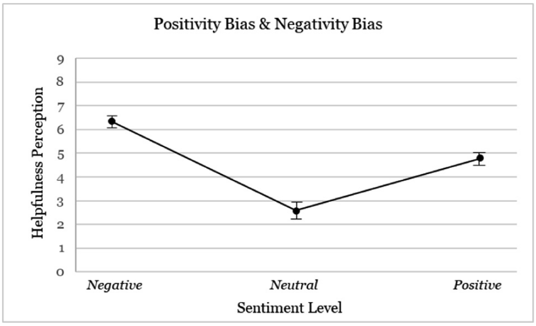

Fig. 4. Positivity bias & negativity bias

In order to test Hypotheses 2a and 3a together, we selected the responses for positive stimulus reviews. As each participant responded to more than one positive review, a repeated-measure ANOVA was performed to examine the helpfulness perception across the three groups. The results showed that the helpfulness perception for positive reviews is not significantly different between 10PT and control groups ($M_{control} = 4.771$, $M_{10PT} = 5.08$, $F(1,115) = 0.47$, $p = 0.6255$), or between 9P1NT and control groups ($M_{control} = 4.771$, $M_{9PT1NT} = 4.571$, $F(1,127) = 0.49$, $p = 0.6135$). Thus, Hypotheses 2a and 3a are rejected, yet we still see the difference in their marginal effect as shown

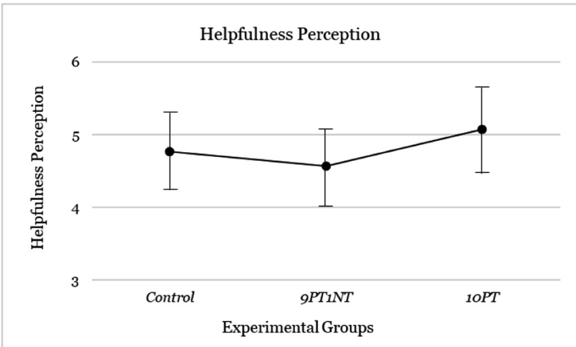

Fig. 5. Helpfulness perception for positive reviews

in Fig. 5 – helpfulness perception for positive reviews is slightly higher (but insignificant) for products shown with all positive tags.

We use the responses for negative stimulus reviews to test Hypotheses 2b, 3b and 4 simultaneously. Again, we performed a repeated-measure ANOVA. The results showed the helpfulness perception for negative reviews is significantly different across the three versions ($M_{control} = 6.307$, $M_{9PT1NT} = 6.071$, $M_{10PT} = 6.741$, $F\ (2{,}180) = 3.16$, $p = 0.045$). Two separate t-tests were performed to examine the two with-tag-function groups comparing to the control group. Results showed that in 10PT group, the helpfulness perception is significantly higher than that in control group ($t\ (116) = 1.8026$, $p = 0.037$). And it showed no difference for helpfulness perception in between the 9PT1NT group and the control group ($t\ (128) = 0.8995$, $p = 0.815$). Figure 6 shows the differences in helpfulness perception at with 95% confidence intervals.

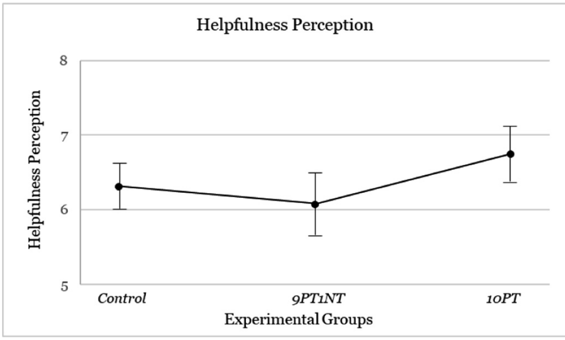

Fig. 6. Helpfulness perception for negative reviews

Therefore, Hypotheses 2b and 3b are rejected, but Hypothesis 4 is supported. The helpfulness perception for negative reviews did not show difference between a typical review tag setting and no-tag-function setting. In contrast, when review tags are shown and all positive, negativity bias is larger comparing to it is in no-tag-function setting.

We also tested on the neutral reviews. Results of an ANOVA test showed no significant difference in helpfulness perception among three groups ($M_{control} = 2.885$, $M_{9PT1NT} = 2.172$, $M_{10PT} = 2.630$, $F(2,89) = 1.47$, $p = 0.236$).

6 Discussion

6.1 Key Findings and Contributions

By directly manipulating the tag function usage, we provide evidence supporting part of our hypotheses. The research has three major findings. First, in general, participants give higher product evaluation when tag function is shown. Second, for positive reviews, tag function does not lead to significant difference in reviews' helpfulness perception. Third, for negative reviews, overwhelming positivity in tags leads to a higher negativity bias comparing to typical tag function appearance (nine positive tags and one negative tag) and no-tag-function situation.

Our study makes the following contributions. First, we fill in the research gap of investigating the impact of the review tag function in online markets. Prior studies on tag function largely focused on algorithms and techniques for review summarization [13, 35], our research contributes to the understanding of the its role in online markets and shows its impact on product evaluation as well as product review's helpfulness perception.

Second, our findings add value to the current understanding of consumers' product and review perception during review consumption. As IS scholars have increasingly recognized the important impact of review texts [10, 36, 37], tag function, as a tool integrating the textual power in reviews, shows its effectiveness in influencing consumers information consumption. Also, our conclusions of helpfulness perception supplement the existing research on the role of review variance. As prior studies reach inconclusive results on the impact of review variance on review helpfulness perception, we found that sellers could benefit from a slight variance of product opinions.

Third, by adapting the attribution theory, our research provided a new theoretical lens to understand the role of tags function in online marketing. While previous studies in the domain are largely focusing on examining online reviews, our paper took both product evaluation and reviews into consideration under the context of tag functions.

6.2 Practical Implications

Though the review tag function is not popularly used in current online markets, our findings provide insights for sellers or platforms in deciding its adoption on popular products. A tag function can not only eliminate information overload and inform sellers of consumers opinions in an aggregated level, but also has the potential of offering consumers the most important aspects for considering a product, which might in turn influence the product evaluation and purchase intention.

More specifically, a typical tag function appearance will produce the best performance of product reviews, enhancing product evaluation and preventing overreaction to the positive or negative reviews. As consumers have the tendency of looking for negative comments even with all positive situations, sellers shall not concern too much about a few negative comments on unimportant features or attributes. To the contrary, they should avoid presenting only positive tags on their product pages, in case their mere negative comments would backfire on the good product reputation.

In addition, various empirical results have found the helpfulness perception of reviews are influenced by many factors [6, 14, 25]. Supplementing their research, our findings focus on tag function, which is a promisingly useful application in online markets. Since we found that the adoption of tag function would bring higher negativity bias when all tags are positive, practitioners are encouraged to reconsider their adoption decision, so that they would not be backfired by their well-managed positive reviews.

6.3 Limitations

Our study is not without limitations. Although we studied two appearances of the review tag function in online markets which are more commonly seen in online markets, other appearances could also be common and worth examining. Based on our result, it is interesting to learn how an increased portion of negative review tags influence the consumers' product and review perceptions comparing to no-tag-function situation.

In studying the impact of consensus information in consumers' causal attribution on product reviews, we emphasized only on the sample representativeness for consensus, leaving other possible elements being unexamined, such as the magnitude and relevance of consensus [22].

Also, our target prototype is the review tag function for a computer product on Tmall.com. Generalizability issue of the research could be raised due to the differences existing in product type [38], culture and languages as well as in shopping conventions. Future research could draw on the function usage on other products or platforms to explore its role in perceptual and behavioral outcomes of consumers.

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References

1. Mudambi, S.M., Schuff, D.: What makes a helpful online review? A study of customer reviews on Amazon.com. MIS Q. **34**(1), 185–200 (2010). https://doi.org/10.2307/20721420
2. Dimoka, A., Hong, Y., Pavlou, P.A.: On product uncertainty in online markets: theory and evidence. MIS Q. **36**(2), 395–426 (2012)
3. Dellarocas, C.: The digitization of word of mouth: promise and challenges of online feedback mechanisms. Manag. Sci. **49**(10), 1407–1424 (2003). https://doi.org/10.1287/mnsc.49.10.1407.17308
4. Lu, X., et al.: Promotional marketing or word-of-mouth? Evidence from online restaurant reviews. Inf. Syst. Res. **24**(3), 596–612 (2013). https://doi.org/10.1287/isre.1120.0454

5. Forman, C., Ghose, A., Wiesenfeld, B.: Examining the relationship between reviews and sales: the role of reviewer identity disclosure in electronic markets. Inf. Syst. Res. **19**(3), 291–313 (2008). https://doi.org/10.1287/isre.1080.0193
6. Yin, D., Mitra, S., Zhang, H.: Research note—when do consumers value positive vs. negative reviews? An empirical investigation of confirmation bias in online word of mouth. Inf. Syst. Res. **27**(1), 131–144 (2016). https://doi.org/10.1287/isre.2015.0617
7. Sun, M.: How does the variance of product ratings matter? Manag. Sci. **58**(4), 696–707 (2012). https://doi.org/10.1287/mnsc.1110.1458
8. Ba, S., Pavlou, P.A.: Evidence of the effect of trust building technology in electronic markets: price premiums and buyer behavior. MIS Q. **26**(3), 243–268 (2002). https://doi.org/10.2307/4132332
9. Yan, X., Wang, J., Chau, M.: Customer revisit intention to restaurants: evidence from online reviews. Inf. Syst. Front. **17**(3), 645–657 (2015). https://doi.org/10.1007/s10796-013-9446-5
10. Archak, N., Ghose, A., Ipeirotis, P.G.: Deriving the pricing power of product features by mining consumer reviews. Manag. Sci. **57**(8), 1485–1509 (2011). https://doi.org/10.1287/mnsc.1110.1370
11. Chen, P.-Y., Hong, Y., Liu, Y.: The value of multi-dimensional rating systems: evidence from a natural experiment and randomized experiments. Manag. Sci. (2017). https://doi.org/10.1287/mnsc.2017.2852
12. Pan, Y., Zhang, J.Q.: Born unequal: a study of the helpfulness of user-generated product reviews. J. Retail. **87**(4), 598–612 (2011). https://doi.org/10.1016/j.jretai.2011.05.002
13. Hu, M., Liu, B.: Mining and summarizing customer reviews. In: Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM (2004)
14. Hu, N., Pavlou, P.A., Zhang, J.: On self-selection biases in online product reviews. MIS Q. **41**(2) (2017). https://doi.org/10.25300/misq/2017/41.2.06
15. Heider, F.: The Psychology of Interpersonal Relations. Psychology Press, London (1958)
16. Försterling, F.: Attributional conceptions in clinical psychology. Am. Psychol. **41**(3), 275 (1986). https://doi.org/10.1037/0003-066X.41.3.275
17. Kelley, H.H., Michela, J.L.: Attribution theory and research. Annu. Rev. Psychol. **31**(1), 457–501 (1980). https://doi.org/10.1146/annurev.ps.31.020180.002325
18. Kelley, H.H.: Attribution in social interaction. In: Jones, E.E., et al. (eds.) Attribution: Perceiving the Causes of Behavior. Lawrence Erlbaum Associates, Inc., Hillsdale (1987)
19. Kelley, H.H.: Attribution theory in social psychology. In: Nebraska Symposium on Motivation. University of Nebraska Press (1967)
20. Kelley, H.H.: The processes of causal attribution. Am. Psychol. **28**(2), 107 (1973). https://doi.org/10.1037/h0034225
21. McGill, A.L.: Context effects in judgments of causation. J. Pers. Soc. Psychol. **57**(2), 189 (1989). https://doi.org/10.1037/0022-3514.57.2.189
22. Kassin, S.M.: Consensus information, prediction, and causal attribution: a review of the literature and issues. J. Pers. Soc. Psychol. **37**(11), 1966 (1979). https://doi.org/10.1037/0022-3514.37.11.1966
23. Wells, G.L., Harvey, J.H.: Do people use consensus information in making causal attributions? J. Pers. Soc. Psychol. **35**(5), 279 (1977). https://doi.org/10.1037/0022-3514.35.5.279
24. He, S.X., Bond, S.D.: Why is the crowd divided? Attribution for dispersion in online word of mouth. J. Consum. Res. **41**(6), 1509–1527 (2015). https://doi.org/10.1086/680667
25. Chen, Z., Lurie, N.H.: Temporal contiguity and negativity bias in the impact of online word of mouth. J. Mark. Res. **50**(4), 463–476 (2013). https://doi.org/10.1509/jmr.12.0063

26. Lombard, M., Snyder-Duch, J., Bracken, C.C.: Content analysis in mass communication: assessment and reporting of intercoder reliability. Hum. Commun. Res. **28**(4), 587–604 (2002). https://doi.org/10.1111/j.1468-2958.2002.tb00826.x
27. Krippendorff, K.: Content Analysis: An Introduction to Its Methodology. Sage, Thousand Oaks (2004)
28. Cohen, J.: Weighted kappa: nominal scale agreement provision for scaled disagreement or partial credit. Psychol. Bull. **70**(4), 213 (1968). https://doi.org/10.1037/h0026256
29. Sen, S., Lerman, D.: Why are you telling me this? An examination into negative consumer reviews on the web. J. Interact. Mark. **21**(4), 76–94 (2007). https://doi.org/10.1002/dir.20090
30. Yin, D., Bond, S., Zhang, H.: Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. MIS Q. **38**(2), 539–560 (2014). https://doi.org/10.25300/MISQ/2014/38.2.10
31. DeVellis, R.F.: Scale Development: Theory and Applications, vol. 26. Sage Publications, Thousand Oaks (2016)
32. Nunnally, J.C.: Psychometric Theory, 3rd edn. McGraw-Hill, New York (1967)
33. Hair, J.F., et al.: Multivariate Data Analysis: A Global Perspective, vol. 7. Pearson, Upper Saddle River (2010)
34. Fornell, C., Larcker, D.F.: Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. **18**(1), 39–50 (1981). https://doi.org/10.2307/3151312
35. Tsaparas, P., Ntoulas, A., Terzi, E.: Selecting a comprehensive set of reviews. In: Proceedings of the 17th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining. ACM (2011)
36. Chevalier, J.A., Mayzlin, D.: The effect of word of mouth on sales: online book reviews. J. Mark. Res. **43**(3), 345–354 (2006). https://doi.org/10.1509/jmkr.43.3.345
37. Bao, Z., Chau, M.: A schema-oriented product clustering method using online product reviews. In: International Conference on Information Systems (ICIS 2016) (2016)
38. Huang, P., Lurie, N.H., Mitra, S.: Searching for experience on the web: an empirical examination of consumer behavior for search and experience goods. J. Mark. **73**(2), 55–69 (2009). https://doi.org/10.1509/jmkg.73.2.55

Antecedents and Consequences of App Update: An Integrated Research Framework

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Abstract. E-commerce firms now compete intensively on mobile applications (apps). The transparency of digital environment has made customers and competitors as major external driving forces of app updates. However, app-related studies mainly focus on how to succeed in the hyper-competitive app market and how platform governance influence app evolution, overlooking the interaction among customers, competitors, and focal firm that shapes continuous app updates. Moreover, extant studies on app updates has drawn inconsistent conclusions regarding the impact of update frequency on market performance. We, therefore, proposed an integrated research framework to explore antecedents and consequences of app updates. We empirically test it by tracking customer reviews, updating notes, and ranks of 20 iOS apps within travel category in China for 60 months. The results indicate that the extreme sentiment expressed by customers will urge focal firm to update frequently and the focal firm will incorporate useful customer feedbacks to release a major update. Interestingly, we find that focal firm is reluctant to release superfluous updates and perform major updates if there are more high-ranking competitors update earlier. Our findings also testify the dual role of the number of total apps focal firm owns in facilitating update frequency and volume, as well as constraining days between two subsequent releases. Lastly, frequent updates will induce a higher degree of rank volatility, while long update intervals will decrease ranks. Our study has important implications for firms to succeed in the fierce competition in mobile commerce.

Keywords: Mobile commerce · Mobile apps · Competition · App updates
Digital business strategy

1 Introduction

Mobile commerce has become one of the dominant strategies for most firms currently. The volume of mobile transactions has surpassed that of PC-based online shopping[1]. Mobile applications (shortened as *apps* hereafter), the primary facilitator of mobile transactions, therefore are important intermediaries for e-commerce firms to retain

[1] Data from State of Mobile Commerce: http://www.criteo.com/media/5333/criteo-mobilecommerce report-h12016-us.pdf.

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customers and thus gain profits. Besides, the low developing costs and easy entry to app markets have resulted in hyper-competition among e-commerce firms as for apps. Proper app update (i.e., releasing a new version of an existing app) which carries out focal firm's business strategy envisions represents a natural way to thrive in such hyper-competitive environment. However, apart from the focal firm itself that determines frequency or volume of app updates, the transparency of digital environment has amplified the effects of customers and competitors on focal firm's app updates. For example, the focal firm could incorporate customers' feedbacks which are critical demand-side knowledge to introduce new functionalities. Those functionalities may not be introduced without the endeavor of responding to customers' feedbacks. Furthermore, there is a paradox of how frequently to update since the consequences of app updates are not clear. On the one hand, the focal firm needs to update frequently to keep up with its rivals and gain temporal competitive advantages. On the other hand, overly frequent updates would induce negative responses of customers [1]. Therefore, it is important for e-commerce firms to understand how proactively react to customers and competitors impact the updates of their apps and the consequences of such updates.

A mobile app is application software that can be installed and run on portable digital devices such as smartphones and tablets [2]. Prior studies on *software management* predominantly focus on initial stages of system's lifecycle (e.g., IT strategy formulation, implementation, adoption, etc.) and less on system evolution [3]. Costs and complexity related to software maintenance increase as the system evolves. Thus, researchers dedicated to studying how to reduce costs regarding software upgrades, such as optimal patch-release/update cycle [4], expected time to perform major upgrades [5, 6]. App updates are also a particular phenomenon of system evolution [1, 7]. Nevertheless, digital technologies enable developers to update their apps that introduce new features with low costs and efforts [8]. Moreover, compared with traditional systems that are normally large-scale and proprietary, apps mostly are micro applications and market-oriented [9]. The market-oriented nature and the transparency of digital environment have amplified the impact of customers and competitors on focal app's update. Therefore, app updates offer us a unique opportunity to understand how customers, competitors, and focal firm jointly influence the evolution of apps.

Moreover, app markets are epitomized by a high degree of competition and skewed outcome of app success. Therefore, much of attention in prior *app-related studies* has been drawn on determinants of the market performance of apps [10–12], and market strategies (e.g., price formulation and freemium strategy) [2, 13]. Although these studies help developers or firms to achieve better performance in app markets, there is a paucity of studies that have investigated the antecedents of app updates. Recently, viewing apps as essential components to software platforms (e.g., Firefox), some scholars have investigated how platform governance influence app evolution [14, 15]. However, given the market-oriented nature of apps for e-commerce firms and intense interaction with customers and competitors induced by the transparency of digital environment, focusing on the higher level of platform ecosystem masks such interaction.

Furthermore, extant studies on *app updates* have drawn inconsistent conclusions regarding the impact of update frequency on market performance. The majority holds that update more frequently would significantly improve apps' market performance, e.g., downloads [11, 16], user ratings [15, 17], survivals in app markets [12, 18]. However, some recent studies have found the negative impact of frequent updates [1, 14]. For example, Feorderer and Heinzl [1] found that feature update would attract new consumers to increase app downloads while alienate existing ones to post more negative ratings. These inconsistent results could not give e-commerce firms adequate evidence on the rate at which and the extent to which should they update their apps to gain superior market performance.

Therefore, in this study, we explore two research questions to address above research gaps: (1) *how do customers, competitors, and focal firm jointly affect app updates*, and (2) *what is the consequence of such updates on app performance?*

Drawing on literature from the online review, Red Queen Competition, software management as our theoretical foundations, we proposed an integrated research framework to investigate the antecedents and consequences of app updates. In terms of the antecedents, we first conceptualize customer effect as customers' sentiment and feedbacks, competitor effect as competitors' move and performance. And we posit that while focal firm proactively responds to customers and competitors, the total apps focal firm owns acts as an indicator of resource facilitator and resource constraints that pushing forward and holding back those responses. Moreover, we use update rates and update volume to characterize app updates. Regarding the consequences of app updates, rank and rank volatility are proposed to better capture the multi-dimensional nature of app performance.

We further conduct a two-stage empirical study with a panel dataset collected from Apple's App Store and econometric analyses. The dataset consists of 495712 customer reviews, updating notes of each version, the total number of apps provided by the same firm, feature history on App Store, and daily rank for 20 apps within travel category in China. And the observation window ranges from January 1, 2012, to December 31, 2016, i.e., 60 months in total. Then, Poisson model, negative binomial (NB) model for panel data, and OLS regression with panel-corrected standard error are justified in the estimation procedure.

Our empirical analysis yields four key findings. First, the extreme sentiment expressed by customers will urge focal firm to update frequently and the focal firm will incorporate useful customer feedbacks to release a major update. Second, interestingly, we find that if there are more high-ranking competitors update early, the focal firm is reluctant to update frequently and perform major updates, suggesting competitive inertia under hyper-competitive environment. Third, the number of total apps focal firm owns facilitates update frequency and volume, while it will constrain days between two subsequent releases. Fourth, frequent updates will induce higher volatility of ranks, while long update intervals will decrease ranks.

The rest of the paper is structured as follows. We begin by articulating theoretical foundation, proposing hypotheses and our research framework. We then elaborate our data, variables, and econometric analysis. A summary of results follows. In the end, we present our conclusions and discussions.

2 Theoretical Foundations and Research Framework

In this section, we draw literature on the online review, Red Queen competition and software management to shed light on our theoretical foundation, propose our hypotheses and research framework as shown in Fig. 1.

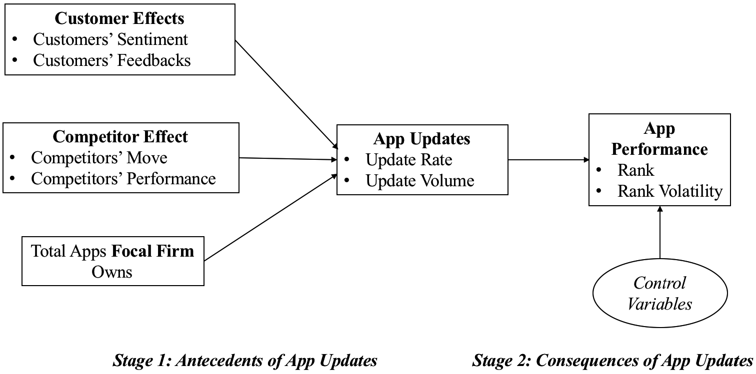

Fig. 1. The integrated research framework of app updates

App updates are related to decisions on update rate and update volume (i.e., how much features added in each update [4–6]). We define ***app performance*** as the overall ranking and rank volatility in app markets. Rank is a comprehensive indicator of the market performance of an app since it reflects customers' reaction to app update by incorporating multiple dimensions such as downloads, active usage etc.

On the one hand, the faster update of an app indicates quick responses to market opportunities, thus focal firm could potentially better meet a known customers' needs and discover unmet ones [15], resulting enhancements of its overall ranking. On the other hand, the faster update of an app may bring about inconsiderate new functionalities and inadequate pretests which would harm customers' use experiences. Thus, frequent updates would induce a higher degree of rank volatility.

Moreover, update volume represents the extent to which changes introduced with an update. More functionalities introduced or enhanced within each new version would attract more customers and retain existing ones, resulting in better ranking. However, more changes made to an update would lead to more additional cognitive resources required for customers to adapt to those changes, which would increase customers' learning costs. If the costs exceed utility, high update volume would potentially induce customers' negative responses, resulting high ranking volatility. Based on above discussion, we hypothesize that:

Hypothesis 1a(Update Rate): Faster update of an app would improve its overall ranking, while instigating higher degree of rank volatility.
Hypothesis 1b(Update Volume): More functionalities introduced or enhanced within an app update would improve its overall ranking and instigate higher degree of rank volatility.

Customer effect lies twofold: customers' sentiment and feedbacks. First, we posit that extreme sentiment expressed by customers about the app would stimulate focal firm to update faster and introduce more functionalities within an app update. A positive sentiment such as praises or identification of existing features would lead spirals upward and motivate firms to provide a better version and more features. On the contrast, firms tend to respond to negative sentiment more quickly because of the negative bias [19]. Secondly, customer feedback on the app are the critical source of demand-side knowledge [20]. Those feedbacks are valuable for focal firms to further improve their apps. However, if more feature requests provided by users, the focal firm takes time to figure out the original idea of users and what should be satisfied first. Thus, it would constrain the rate of updates while helps focal firm provide more functionalities by incorporating demand-side knowledge. Based on above discussion, we make the following conjecture:

Hypothesis 2: Customers' sentiment and feedbacks would have a significant impact on focal firm's app updates.
Hypothesis 2a(Customer Sentiment): More extreme sentiment expressed by customers would lead to faster app updates and more functionalities introduced within an app update.
Hypothesis 2b(Customer Feedbacks): More feedbacks provided by customers would reduce the rate of app updates while instigating more functionalities introduced within an app update.

Competitor effect on focal firm's app updates lies twofold: competitors' early updates and better visibility. The hyper-competitive nature of app market results in *Red Queen competition* [3, 21, 22] among apps. If competitor updates its app earlier, customers can potentially enjoy enhanced services and achieve better user experience. Thus, competing apps might rank better and gain favorable visibility to customers, causing competitive pressures to the focal firm. Thus, if there are more competitors update their apps and gain better performance, the focal firm would update its app more frequently, and introduce with more functionalities to catch up with its cohorts of rivals. We, therefore, hypothesize that:

Hypothesis 3a(Competitors' Move): Competitors' early app updates would stimulate focal firm update more frequently, and introduce more functionalities within an app update.
Hypothesis 3b(Competitors' Performance): Competitors' better performance would stimulate focal firm update more frequently, and introduce more functionalities within an app update.

While focal firm proactively responds to customer feedbacks and competitors' move, ***the number of total apps focal firm owns*** play a role in holding back or pushing forward those responses. It is an indicator of firm's mobile strategy. On the one hand, plausibly speaking, the more apps a firm owns at the same time, the more investment focal firm makes in the app market. Thus, it would facilitate more functionalities introduced within each update. On the other hand, owing to resource scarcity, the more apps focal firm owns would increase the likelihood of internal competition of resources, constraining rate of updates (i.e., decrease update frequency and lengthen interval of days between two subsequent releases). Accordingly, we hypothesize that:

Hypothesis 4a(Facilitating Effect): The more apps focal firm owns would facilitate more functionalities introduced within an app update.
Hypothesis 4b(Constraining Effect): The more apps focal firm owns would constrain the rate of updates.

3 Data and Methods

To empirically test above research framework, we choose online travel industry in China as our research context. 20 online travel apps from Apple's App Store are selected based on an explicit sampling strategy. Then, we provide an overview of our dataset, describe variables and measurements. Model specification and econometric models are discussed in the end.

3.1 Data Collection

We choose online travel industry in China as our research context. Most of the online and traditional travel agencies have started to develop their apps since 2012 and updated their apps frequently to compete fiercely within the industry. Moreover, 78.3% transactions are achieved through mobile in 2016[2]. The intense usage and review mechanism provided by app markets leave a large volume of app reviews which enables us to capture customers' sentiment and feedbacks on a certain app. And firms in this industry attach much importance to those reviews and proactively respond to customers' feedbacks.

We further restrict our data analysis to 20 iOS apps in travel category over a period from January 2012 to December 2016, i.e., 60 months in total. The market share of iPhone in China remains top 3 from 2011 to 2015[3]. And App Store that serves as an online market for mobile apps compatible with the iOS platform has been the second largest one worldwide and provides more than 2.2 million apps as of March 2017[4]. Moreover, considering the inaccessibility of Google Play and no standard way of distributing Android app in China, App Store offers a unified distribution channel for app releasing and downloads. Detailed app information, customer reviews, and ranks are also available on App Store.

To ensure comprehensiveness and representativeness of apps, we selected apps that rank top 100 on the free chart within travel category for at least 50 times out of 60 months. Then, since we focus on apps with commerce features, we eliminated infomediary apps, travel-assistant apps, apps removed from App Store, and unrelated ones. Accordingly, we got 20 apps as our sample. This sampling strategy satisfies the

[2] https://www.analysys.cn/analysis/22/detail/1000268/

[3] http://www.idc.com/getdoc.jsp?containerId=prAP41028416

[4] Data from Statista 2017: https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/

criterion of *resource similarity and market commonality* established in competitive dynamics [23] and the argument that apps compete within the same category in digital innovation literature [8, 12].

Subsequently, we collected data from Apple's App Store on 20 sample apps between January 1, 2012, and December 31, 2016, and constructed a panel dataset for analysis. Specifically, our data collection consists of three aspects. Firstly, we obtained *495712* unique reviews on our sample apps. The data involves reviewer's ID, review date, review title, review content, and rating. The rating scheme presented in App Store is some "stars" from 1 up to 5. Secondly, app details including app name, description, initial release date and updating notes of each version, number of apps provided by the same firm and feature history on App Store were collected. Also, we collected daily top free rankings within travel category in China.

3.2 Variables and Measurements

Dependent Variables. We have two primary dependent variables (DV): *app updates* and *app performance*. App updates include: (1) *Update Rate*. It's measured by two metrics, i.e., update frequency and update interval. Update frequency is measured by the number of updates for app i at month t. Update interval is measured by the interval of days between subsequent release; (2) *Update Volume*. Since updating notes would list updating content, we calculated the number of updating functionalities to measure it for app i at month t. If update volume is large, it indicates that a lot of functionalities has been enhanced or introduced within this version.

App performance is estimated in two complementary ways: (1) *Rank* is computed on a monthly basis. Lower rank means better performance. We then inverted it to give us intuitional judgments, marked as *Inversed Rank* in the result table; (2) *Rank Volatility* which is measured by standard deviation of ranks for app i at month t. Apple's App Store ranking is a comprehensive indicator of market performance for an individual app. Despite the fact that the ranking algorithm remains a black box to the public, determinants include downloads [12, 24], factors, such as active usage, app searches, rating, and reviews, etc. [2] since 2011[5]. Moreover, rank has been assumed to be a valid proxy for app demand in prior studies [11, 12, 25].

Independent Variables. We construct three sets of independent variables: (1) customer-related, (2) competitor-related, and (3) focal-firm-related variables. And we dynamically calculated all variables for app i at month t.

Customer reviews on app often contain feedbacks valuable both for firms to improve user experience and other customers' decision on downloading the app. Such feedback regularly includes feature requests, bug reports, praises or complaints [7]. We then adopt well-established metrics (i.e., rating variance, valence, positive and negative review volume) [26, 27] to characterize sentiment of customer reviews on the app and average review length as a text-based feature to reflect information abundance of customer feedbacks. (1) *Rating Variance*: standard deviation of rating. It's a measure of

[5] http://www.adweek.com/digital/apple-app-store-ranking-changes/?red=im

dispersion in opinions. (2) *Valence*: average ratings of posted reviews. (3) *Average Review Length*: average length of reviews by words. (4) *Positive Review Volume*: number of reviews with a rating higher than three and those lesser are calculated as (5) *Negative Review Volume*.

Competitor-related variables encompass two variables. (1) *Competitors' Move* reflects competitors' move on app updates, which is operationalized by the number of competitors that release a new app version before the focal app. (2) Competitors' Performance is better performance of competing apps, which is operationalized by the number of competitors that rank ahead of the focal app.

The focal-firm-related variable is *Number of Total Apps*. Number of Total Apps are apps offered by the same firm. We calculated Number of Total Apps a firm owns across different platform (e.g., iOS, Google Play, etc.) and different publisher account.

Control Variables. We also controlled four variables that can influence app ranks: (1) *App Age*: number of days passed after app *i* was released. (2) *Bug Fix*: whether current version involves bug fixing (1) or not (0). (3) *Promotion*: whether latest version includes promotion, discount, bonus (1) or not (0). (4) *Features on App Store*: whether focal app in the current month is featured by app store (1) or not (0).

3.3 Econometric Analysis

Since our study involves two sets of dependent variables (i.e., app updates and app performance), we conduct model specification and construct econometric models respectively.

App Updates

Model Specification. All of our dependent variables regarding app updates are count variables which are discrete and nonnegative, making traditional ordinary least square (OLS) regression inappropriate. Poisson regression and negative binomial regression are common methods used to estimate such model [28]. Moreover, except update frequency data, we observed over-dispersion in two other DV data. Therefore, we apply Poisson regression for *update frequency* (labeled as Model 1) and negative binomial regression for *update interval, and update volume* (labeled as Model 2, 3 respectively).

Besides, our panel data enables us to use fixed effects (FE) or random effects (RE) models to address unobserved individual-specific effects (e.g., firm's management policy, culture etc.). Those effects may account for endogeneity issues [29]. However, RE model relies on a restrictive assumption that independent variables are uncorrelated with individual effects. Hausman [30] specification test checks the hypothesis that FE and RE model produce consistent estimators. In our case, Hausman test was insignificant for Model 1, 2 and was significant for Model 3. Accordingly, we adopted RE for Model 1, 2 and FE for Model 3.

Econometric Models. We controlled ranks in the previous month for the focal app and estimate the following model using corresponding econometric techniques.

$$Y_{i,t} = \alpha + \beta \text{Customer}_{i,t-1} + \gamma \text{Competitor}_{i,t-1} + \delta \text{Focal}_{i,t} + \rho Control_{i,t-1} + u_i + \varepsilon_{i,t} \quad (1)$$

where < i, t > represents app-month combination, Y represents a vector of app update variables (i.e., *Update Frequency, Update Interval, and Update Volume*), *Customer* represents a vector of lagged variables related to customer review (i.e., *Rating Variance, Valence, Average Review Length, Positive Review Volume, and Negative Review Volume*), *Competitor* represents a vector of lagged variables related to competitor effect (i.e., *Competitors' Move and Competitors' Performance*), *Focal* represents focal-firm-related variable (i.e., *Number of Total Apps*), Control represents the control variable for ranks, u_i denotes the unobserved individual effect, $\varepsilon_{i,t}$ denotes the remaining stochastic disturbance term, and $\alpha, \beta, \gamma, \delta$ are the regression model coefficients.

App Performance

Model Specification. We executed OLS regression with panel-corrected standard error to examine the relationship between four sets of independent variables and app performance. Recall that we inversed *Rank* (labeled as Model 4) to give us intuitional justification of effects on app performance and we calculated the standard deviation of ranks to measure *Rank Volatility* (labeled as Model 5). Thus, the DVs are transformed into continuous ones, indicating OLS regression is suitable. Besides, we performed Wooldridge tests to check whether there is the serial correlation [29], Wald tests to check the existence of heteroscedasticity [31], and Breusch-Pagan LM test to examine the dependence between panel units. The results indicate the existence of group-wise heteroscedasticity and cross-sectional correlation in our data. We, therefore, followed the prescription of Beck and Katz [32] and conducted panel-corrected standard error to address above issues.

Econometric Models. Despite the effects of app updates on performance, customer sentiment and feedbacks, competitors' move, and Number of Total Apps focal firm owns could also affect app performance. We, therefore, controlled customer-related variables for WOM effects and competitor-related variables for competition effects and Number of Total Apps for individual heterogeneity. We then estimate the following FE model.

$$Y_{i,t+1} = \alpha + \varphi \text{Update}_{i,t} + \eta \text{Control}_{i,t} + \lambda u_i + \varepsilon_{i,t} \quad (2)$$

where < i, t > represents app-month combination, Y represents a vector of app performance variables (i.e., *Inversed Rank, and Rank Volatility*), *Update* represents a vector of lagged variables related to app update,*Control* represents a vector lagged control variables (i.e., *review-related variables, competitor-related variables, Number of Total Apps, and other control variables: App Age, Bug Fix, Promotion and Features*), u_i denotes app dummies to control the unobserved individual effect, ε_{it} denotes the remaining stochastic disturbance term, and α, φ, η are the regression model coefficients.

4 Results

Table 1 summarizes the descriptive statistics for all variables. Furthermore, we computed the variance inflation factors (VIF) to test for any possible multicollinearity. The VIFs for all variables are less than the critical value of 10 (the highest is 2.25), eliminating potential multicollinearity problems.

Table 1. Descriptive statistics

Variables	Observations*	Mean	Std. Dev	Min	Max
1. Rating variance	1162	1.13	0.49	0	2
2. Valence	1162	3.93	1.08	1	5
3. Average review length	1162	22.08	18.71	1.5	479.5
4. Positive review volume	1162	390.9	1457	0	27040
5. Negative review volume	1162	36.37	103.5	0	1367
6. Competitors' move	1181	8.34	5.36	0	77
7. Competitors' performance	1181	9.35	5.71	0	19
8. Update frequency	1181	0.98	0.80	0	5
9. Update interval	842	335.2	3516	1	42357
10. Update volume	1181	3.83	3.99	0	28
11. Number of total apps	1181	10.37	13.56	0	61
12. App age	1181	1233	2081	0	40933
13. Bugfix	842	0.36	0.48	0	1
14. Promotion	842	0.39	0.49	0	1
15. Features	1181	0.39	0.24	0	1
16. Rank	1181	28.87	23.21	1	201.2
17. Rank volatility	1181	4.81	4.68	0	38.79

*Note: The observations are not identical due to lack of observation in certain months and inconsistency of multiple data sources.

Table 2 presents panel regression for models of app updates. As we can see from Table 2, customer-related variables have significant effects on app update frequency, update interval and update volume. Specifically, coefficients of *rating variance* are positive and statistically significant on update frequency and update volume, suggesting that firms tend to perform frequent updates with more updating items provided if there are incongruent opinions about the quality of the last version. Coefficients of *valence* are positive and statistically significant on update frequency, interval, and volume. This finding indicates that all else being equal, the high average rating given by customers on the last version will motivate the focal firm to update frequently with more updating functionalities provided while increasing days between two subsequent releases. Coefficients of *positive review volume* are negative and statistically significant on update frequency and interval, while coefficients of *negative review volume* are statistically positive on update frequency, negative on update interval. This finding indicates negative bias on app reviews, i.e., firms proactively response to negative

Table 2. Results of panel regression for app updates

	Variables	Model 1	Model 2	Model 3
		Update frequency	Update interval	Update volume
Control variables	Inversed rank$_{t-1}$	0.26 (0.17)	0.40 (0.32)	**0.44*** (0.26)
Customer-related variables	Rating variance	**0.14**** (0.06)	–0.11 (0.09)	**0.25***** (0.07)
	Valence	**0.11***** (0.03)	**0.10**** (0.05)	**0.17***** (0.04)
	Average review length	0.002 (0.002)	**0.007**** (0.003)	**0.002**** (0.001)
	Positive review volume	**–2.28e-05*** (1.27e-05)	**– 0.00018***** (5.02e-05)	–2.76e-05 (2.19e-05)
	Negative review volume	**0.0004*** (0.0002)	**–0.002***** (0.0005)	5.79e-05 (0.0003)
Competitor-related variables	Competitors' move	**–0.07***** (0.007)	0.008 (0.006)	**–0.08***** (0.006)
	Competitors' performance	**–0.01**** (0.005)	**–0.03***** (0.009)	**–0.02***** (0.008)
Focal-firm-related variables	Number of total apps	**0.006***** (0.001)	**–0.02***** (0.003)	**0.01***** (0.003)
	Constant	–0.10 (0.18)	–0.26 (0.28)	–0.05 (0.25)
	Observations	1158	837	1158
	Log likelihood	–1289.41	–4454.86	-2658.03

Note: Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

reviews by update more frequently and decreases days between two subsequent releases. Accordingly, hypothesis 2a is supported.

Coefficients of *average review length* are positive and statistically significant on update interval and volume, suggesting that firms take time to digest rich information on the last version revealed by customers and consider that to perform a major update. Therefore, hypothesis 2b is supported.

Interestingly, competitor-related variables are significant but negative, rejecting hypothesis 3a and 3b. This result suggests that if more high-ranking competing apps update earlier, the focal firm is reluctant to update frequently and perform major updates. This finding suggests the competitive inertia in a hyper-competitive environment which is consistent to the "crowding out" effects with intense competition [8].

Number of Total Apps is positive and significant on update volume. Thus, hypothesis 4a is supported, suggesting the facilitating effect. However, the number of total apps has a significantly positive effect on update frequency while the significantly negative effect on update interval, indicating hypothesis 4b is partially supported.

Table 3. PCSE estimation for app performance

	Model 5.1	Model 6.1	Model 5.2	Model 6.2
Variables	Inversed rank	Rank volatility	Inversed rank	Rank volatility
App Updates				
Update frequency			0.01 (0.01)	**0.45**** (0.22)
Update interval			**–1.05e-06*** (5.66e-07)	–3.28e-05 (3.77e-05)
Update volume			–0.002 (0.001)	–0.03 (0.04)
Controls	YES	YES	YES	YES
Constant	0.13*** (0.02)	4.5*** (1.53)	0.12*** (0.03)	3.61** (1.57)
Observations	842	842	842	842
R-squared	0.78	0.44	0.76	0.44

Note: Panel-corrected standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3 presents PCSE estimation results for models of app performance. Our preliminary results show that *update frequency* is positive and significant on rank volatility, while we didn't find statistically significant evidence on rank. This result is a contrast to the intuition that frequent updates lead to superior ranks, indicating that update frequently will raise the fluctuation of ranks and might diminish customer's experience. Besides, the coefficient of *update interval* is negative and statistically significant in rank, suggesting that firms should shorten days between two releases to increase app visibility and keep customers engaged. Therefore, hypothesis 1a is supported. Moreover, *update volume* doesn't have significant effects on rank and rank volatility, rejecting hypothesis 1b.

5 Conclusions and Discussions

We provided an integrated research framework to study the antecedents and consequences of app updates. We firstly investigated how customers' sentiment and feedbacks, competitors' move and performance, as well as the number of total apps focal firm owns, affect app updates (i.e., update rate and volume). And we subsequently examined the consequences of app updates on corresponding performance (i.e., rank and rank volatility). Those relationships are validated using a panel data and responding econometric analysis.

Overall, customers' sentiment and feedbacks have significant effects on app updates. In particular, the overall valence of customer feedback on the current version will urge focal firm to update quickly. More feedbacks provided by customers will drive the focal firm to perform a major update, introducing more functionalities within that update. Interestingly, we found that focal firm is reluctant to update regularly and perform major updates if more high-ranking competitors update earlier. This finding suggests competitive inertia under hyper-competitive environment, which is consistent with the "crowding out" effect of intense competition [8]. Besides, the number of total apps plays a dual role in that it contributes to updating frequency and volume, while it will constrain days between two subsequent releases. Lastly, in contrast to the intuition that frequent updates lead to superior performance, our results indicate that update frequently will raise rank volatility and thus might diminish customers' experience. We also found that the long interval of days between two subsequent releases will decrease app's rank, suggesting firms should shorten update intervals to increase app visibility and keep the customer engaged. However, we didn't find any significant effects of update volume on app performance.

This paper contributes to the literature in two ways. First, based on the market-oriented nature of apps for e-commerce firms, we proposed an integrated research framework for antecedents and consequences of app updates by explicitly incorporating the impacts of customers and competitors on app updates. Previous app-related studies mainly focus on how to succeed in app markets [10, 11], market strategies [13], and how platform governance affect app evolution [14, 15], overlooking the intense interaction with customers and competitors which are crucial to explaining the continuous app evolution. Drawing on literature on online reviews and Red Queen Competition, we conceptualize customer effect as customers' sentiment and feedbacks, and competitor effect as competitors' move and performance and further empirically justify how those factors and total apps focal firm owns jointly affect app updates. And our findings shed new light on drivers of app evolution apart from platform governance.

Second, we use rank and rank volatility to better capture the multi-dimensional nature of app performance. Although the coefficient is positive, we did not find a significant impact of update frequency on rank. However, our finding indicates that frequent updates will induce a higher degree of rank volatility. Since rank is a comprehensive indicator of downloads and usages, the results suggest that frequent updates could not significantly improve the market performance but could increase the dynamics of its market performance. These findings complement extant studies on app updates that have drawn inconsistent conclusions regarding the impact of update frequency on market performance.

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References

1. Feorderer, J., Heinzl, A.: Product updates: attracting new consumers versus alienating existing ones. In: Proceedings of Thirty Eighth International Conference on Information Systems, Seoul (2017)
2. Liu, C.Z., Au, Y.A., Choi, H.S.: Effects of freemium strategy in the mobile app market: an empirical study of Google play. J. Manage. Inf. Syst. **31**(3), 326–354 (2014)
3. Agarwal, R., Tiwana, A.: Evolvable systems: through the looking glass of IS. Inf. Syst. Res. **26**(3), 473–479 (2015)
4. Cavusoglu, H., Cavusoglu, H., Zhang, J.: Security patch management: share the burden or share the damage? Manage. Sci. **54**(4), 657–670 (2008)
5. Arora, A., Krishnan, R., Telang, R., Yang, Y.: An empirical analysis of software vendors' patch release behavior: impact of vulnerability disclosure. Inf. Syst. Res. **21**(1), 115–132 (2010)
6. Krishnan, M.S., Mukhopadhyay, T., Kriebel, C.H.: A decision model for software maintenance. Inf. Syst. Res. **15**(4), 396–412 (2004)
7. Guzman, E., El-Haliby, M., Bruegge, B.: Ensemble Methods for App Review Classification: An Approach for Software Evolution (N), pp. 771–776 (2015)
8. Boudreau, K.J.: Let a thousand flowers bloom?an early look at large numbers of software app developers and patterns of innovation. Organ. Sci. **23**(5), 1409–1427 (2012)
9. Grover, V., Kohli, R.: Revealing your hand: caveats in implementing digital business strategy. MIS Q. **37**(2), 655–662 (2013)
10. Claussen, J., Kretschmer, T., Mayrhofer, P.: The effects of rewarding user engagement: the case of facebook apps. Inf. Syst. Res. **24**(1), 186–200 (2013)
11. Ghose, A., Han, S.P.: Estimating demand for mobile applications in the new economy. Manage. Sci. **60**(6), 1470–1488 (2014)
12. Lee, G., Raghu, T.S.: Determinants of mobile apps' success: Evidence from the app store market. J. Manage. Inf. Syst. **31**(2), 133–170 (2014)
13. Roma, P., Zambuto, F., Perrone, G.: The role of the distribution platform in price formation of paid apps. Decis. Support Syst. **91**, 13–24 (2016)
14. Song, P.J., Xue, L., Rai, A., Zhang, C.: The ecosystem of software platform: a study of asymmetric cross-side network effects and platform governance. MIS Q. **42**(1), 121–142 (2018)
15. Tiwana, A.: Evolutionary competition in platform ecosystems. Inf. Syst. Res. **26**(2), 266–281 (2015)
16. Comino, S., Manenti, F.M., Mariuzzo, F.: Updates management in mobile applications. Itunes Vs Google Play. Med. J. Malaysia **37**(4), 354–356 (2015)
17. Mcilroy, S., Ali, N., Hassan, A.E.: Fresh apps: An empirical study of frequently-updated mobile apps in the Google Play Store. Empirical Softw. Eng. **21**(3), 1346–1370 (2016)
18. Kajanan, S., Pervin, N., Ramasubbu, N., Dutta, K.: Takeoff and sustained success of apps in hypercompetitive mobile platform ecosystems: an empirical analysis. In: Proceedings of Thirty Third International Conference on Information Systems, Orlando (2012)
19. Yin, D., Mitra, S., Zhang, H.: Research note—when do consumers value positive vs. negative reviews? an empirical investigation of confirmation bias in online word of mouth. Inf. Syst. Res. **27**(1), 131–144 (2016)
20. West, J., Salter, A., Vanhaverbeke, W., Chesbrough, H.: Open innovation: the next decade introduction. Res. Policy **43**(5), 805–811 (2014)
21. Barnett, W.P., Hansen, M.T.: The red queen in organization evolution. Strateg. Manage. J. **17**, 139–157 (1996)

22. Tiwana, A., Konsynski, B., Bush, A.A.: Research commentary—Platform evolution: Coevolution of platform architecture, governance, and environmental dynamics. Inf. Syst. Res. **21**(4), 675–687 (2010)
23. Chen, M.J., Miller, D.: Competitive dynamics: themes, trends, and a prospective research platform. Acad. Manage. Ann. **6**, 135–210 (2012)
24. Lim, S.L., Bentley, P.J.: Investigating app store ranking algorithms using a simulation of mobile app ecosystems. In: IEEE Congress on Evolutionary Computation, Cancún, México (2013)
25. Garg, R., Telang, R.: Inferring app demand from publicly available data. MIS Q. **37**(4), 1253–1264 (2013)
26. Jabr, W., Zheng, Z.Q.: Know yourself and know your enemy: an analysis of firm recommendations and consumer reviews in a competitive environment. MIS Q. **38**(3), 635–654 (2014)
27. Moe, W.W., Trusov, M.: The value of social dynamics in online product ratings forums. J. Mark. Res. **48**(3), 444–456 (2011)
28. Hausman, J., Hall, B.H., Griliches, Z.: Econometric models for count data with an application to the patents-R&D relationship. Econometrica **52**(4), 909–937 (1984)
29. Wooldridge, J.M.: Introductory Econometrics: A Modern Approach. Thompson Publishing, Bethesda (2006)
30. Hausman, J.: Specification tests in econometrics. Econometrica **46**(6), 1251–1271 (1978)
31. Greene, W.: Econometric Analysis. Prentice Hall, Upper Saddle River (2007)
32. Beck, N., Katz, J.N.: What to do (and not to do) with time-series cross-section data. Am. Polit. Sci. Rev. **89**(3), 634–647 (1995)

Is There a Free Lunch? Examining the Value of Free Content on Equity Review Platforms

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Abstract. Planning and advising for financial investment used to be the domain dominated by highly specialized financial analysts. However technological advancements seem to have disrupted this market to a point where free financial investment advice is now available on a variety of web and social media platforms such as amateur investors forums and specialized equity review websites. Since contributors on these platforms vary in terms of their motivation and expertise, we are yet to understand the value of free financial advice available on these platforms. In this research, we focus on the largest equity review website in the US and examine the value of free financial advice available on this platform. Our results simulate the investment using contributors' ideas on S&P 500 listed companies. Our results show that trading based on free financial advice yields good returns on investment.

Keywords: Equity review · Social media · Free content · Stock market

1 Introduction

Technology advancements in recent years have democratized the content generation and dissemination via a range of online channels and platforms, such as YouTube, social media platforms, and crowd-sourced online communities. These platforms provide a broad range of advice/recommendations, from as simple as buying a car to making financial investments. A plethora of content providers and a large number of content consumers have given rise to a range of business models. To attract eyeballs, many platforms provide plenty of free content and hope to convert visitors into paying customers over time. However, we do not know the value of the free content provided via these platforms. It is true that not all the free content can be monetized. Therefore, we only focus on the free content that can be monetized, in particular, the content related to financial investments. In this research, we focus on platforms that provide advice for financial investments and examine the value of free content or advice given on these platforms.

Personal investment advice has been dominated by investment banks, such as Goldman Sachs, for over 150 years. However, networks like Bloomberg established themselves as independent sources of financial news over the last decade. Filling in the void were rapidly growing social media services such as Seeking Alpha [1].

Retail investors solicit information from different sources including financial analyst reports, conventional media like newspapers and social media because studies have

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shown that analyst report, news articles [2], social media [3] can predict the stock market to some extent. In the past, investors relied on traditional information sources such as financial analyst reports, news articles and earnings releases. However, Web 2.0 technologies have facilitated new information structures since last decade [4] and catapulted social media platforms into one of most important information sources.

There is a rich literature on the effect of traditional news media [5–7] and social media on financial markets [8–12]. In addition, different types of social media platforms have been studied, including stock discussion forums and equity review websites.

Social media platforms vary based on the type of contributors. For instance, the contributors on stock discussion forums, such as HotCopper.com and StockTwits.com, can be amateur investors, stock enthusiasts or analysts. There is no clear clue on the identity of these contributors. On the contrary, the contributors of equity review website are stock analysts, traders, economists, academics, financial advisors and industry experts.

Prior studies have established the correlation between stock prices and market sentiments, such as Bullishness Index, generated from social media platforms. Although these studies have shown the correlation between media posts and the market performance, such as stock returns, short sale, etc., it is not clear if investors can trust and invest based on investment advice given on these platforms. Further, we don't know the return on trades made on the basis of these recommendations. In this research, we focus on a social media platform, more specifically an equity review website, Seeking Alpha (https://seekingalpha.com/, SA). Seeking Alpha provides both free and paid content. Since our goal to evaluate the value of free content, we try to simulate investment based on free stock recommendation disclosure in Seeking Alpha and hold it with six different holding periods (30 days to 180 days). By doing this, we answer the research question: What is the value of free content on equity review platforms?

We find that if we had traded based on the free content (articles) from Seeking Alpha, and held the position for 180 days, we would have made money on 71.43% of the stocks which were discussed in SA, whose tickers were among the S&P 500 list during the studied period.

The rest of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data collection. We discuss results in Sect. 4 and conclude in Sect. 5 with direction for future research.

2 Literature Review

Many researchers have shown that traditional media and social media can predict the stock market prices. Tumarkin and Whitelaw [4] are among the first to conduct research on the relationship between social media and stock market and show that changes in investor opinions on the stock discussion forum (RagingBull) are correlated with abnormal industry-adjusted returns on days with abnormally high message activity. Another study also focuses on the stock discussion forum (Yahoo Finance and RagingBull) and finds that stock messages help predict market volatility [9]. Bollen et al.

[3] argue that public mood on Twitter can forecast the Dow Jones Industrial Average. Chen et al. [10] demonstrate that views expressed in both articles and commentaries from an equity review website (seeking alpha) predict future stock returns and earnings surprises. Das and Chen [11] argue that tech-sector postings are related to stock index levels, and to volumes and volatility by using the data from Yahoo's message board. Luo, Zhang, and Duan [13] show that social media metrics are significant indicators of company equity value.

This stream of research is very popular, which attracted researchers' attentions from many disciplines, including marketing, information systems, economics and many other domains. Many studies have shown that consumers' social media interactions and activities have an impact on their buying behaviors, which will ultimately affect firms' sales [14–16]. As we can see that a large number of studies confirm some value in the information provided on a variety of media platforms. However, we don't yet understand which piece of information is valuable and which one is not. In this research, we attempt to examine the value of free content (articles) posted on an equity review website.

Scholars have been intrigued why users contribute to social media platforms? The general notion is that by providing free access, content gain recognition and associated benefits. In fact, a recent study, using data from Seeking Alpha, has empirically shown that contributors gain utility from attention and recognition from contributing articles [10]. Similar research in academic publishing has shown that open access to the research literature can possibly quicken recognition and dispersal of research discoveries [17], and more highly cited articles, and more recent articles, are significantly more likely to be free online [18]. Further, it has been shown that articles whose authors have made their final draft free online are cited a lot more than articles in the same journal and year that have not been made free [19].

On social media and other web platforms, users often do not know opinion leaders or expert providing the advice, and so scholars have questioned why do users trust investment advice from strangers when there is no guarantee on the quality of information available on these platforms? Although source credibility has been demonstrated as a major influence on consumer decisions in offline situations [20–22], consumers in online settings rarely attempt to make assumptions about a source based on the information displayed on his/her online profile (e.g., helpful votes received by a reviewer or the number of reviews published), because they do not find them to be critical to assessing the quality of a product or service [23]. Instead, information quality and base-rate data (rankings and customer ratings) apply a more grounded effect on buyers' appraisal of product quality. We argue that social media platforms allow users to interact with each other and allow publicly visible feedback on the author's contributions. These features enable users to collectively improve the quality of the content.

Since there is a lot of free content available on social media platform, we need to understand the value of this free content. Different people on social media represent different user groups and have different levels of credibility and informativeness. Goldenberg, Han, Lehmann, and Hong [24] find that influential people are considered to have three characteristics: (1) they are convincing; (2) they are experts who know a lot; (3) they have a large number of social ties. In our context, SA's contributors fit in these characteristics quite well. Therefore, we argue that content produced by these contributors is certainly valuable.

Two recent papers studied on SA. Chen et al. [10] show that the percentage of negative words in articles and comments are significantly correlated with subsequent abnormal return with different holding periods. Wang et al. [1] contrast the performance of SA and StockTwits and show that analysis in SA provides more positive correlation with stock performance than user-generated content from StockTwits, even though the correlation is weak. However, it is still not clear whether these trading ideas based on free articles will be profitable if investors trade based on them, as most of the articles don't tell when to buy or sell and when to close the position. In this research, we have tested these concerns by simulating trades.

3 Data

We developed a data collection engine to collect data from one of top equity review websites, Seeking Alpha. In comparison with other equity review websites, contributions on Seeking Alpha come from a broad base of investors and industry experts (buy side) rather than sell side. As of February 2014, the Seeking Alpha had 3 million registered users, and 8 million unique viewers per month [25]. An equity review website is different from stock discussion forums in many ways. First, stock discussion forums often have a limit on the length of a message, and the content is full of slang and abbreviations because contributors are mostly amateur investors. Second, contributors can stay anonymous, and there is no guarantee of quality of the content because these stock discussion forums are open communities with no formal management structure. On the contrary, equity review websites attract contributions (articles) from industry experts and reputed analysts who use formal language and articles do not have a limit on length. Therefore, the quality of the content available on equity review websites is likely to be better than on free flowing stock forums.

Similar to any equity review platform, Seeking Alpha also offers free and pro articles. Pro articles are considered to have more value and users have to pay a subscription fee (USD 2500 per year) to access pro articles. Since our focus is examining the value of free content on these equity websites, we have only focused on free articles. We only focus on those articles that recommend stocks included in Standard & Poor's 500 Index. We have collected data on articles published during 2016-01-01 and 2016-12-31. To avoid using confounding information, we only focus on articles which have disclosure/recommendation for one stock ticker. Table 1 shows the histogram for the number of tickers discussed in an article.

Stock daily prices are collected from Quandl (https://www.quandl.com/) and saved in our database.

4 Simulator for Assessing ROI

We have developed a backtesting system to simulate the real time trading. Our approach is described below:

Table 1. Number of articles published for each stock ticker

Number of articles published	Number of tickers
Between 0 and 40	473
Between 40 and 80	15
Between 80 and 120	10
Between 120 and 160	1
Between 160 and 200	0

1. Each stock is considered separately, which means we simulate the trading for each stock separately. For instance, let's consider AAPL.
2. We get a list of Adjusted Closing price data points of AAPL on a daily frequency from Quandl.
3. We use the disclosure of collected articles on AAPL as the trading strategy to generate trading signals.
   a. All the trading signals are set to 0 at the start, where 0 represents *No Trading*.
   b. If the disclosure is "Long", the trading signal on that date will be updated by +1, which means we buy the discussed stock.
   c. If the disclosure is "Short", the trading signal on that date will be updated by −1, which means we sell the discussed stock.
   d. If the disclosure is "No Position", then we do not update the trading signal.

If there is any article about AAPL that is posted on a non-trading date, then the trading signal will be postponed to the following trading date [10]. We will close the position with different holding periods (30 days, 60 days, 90 days, 120 days, 150 days and 180 days). If the trading signal is updated +1/−1 based on articles' disclosure/recommendation, then we will update the trading signals by −1/+ 1 after the predefined holding dates.

4. We use the trading signals to generate a sequence of positions. Each date's signal is multiplied by 100 to get the corresponding position. For instance, if the signal for AAPL on 2016-01-07 is +1, then the position for that day is +100, which means we buy 100 shares of AAPL on that date. Of course, we need to sell 100 shares AAPL accordingly on 2016-02-06 if the holding period is 30 days.
5. We set our initial capital as $100,000.
6. On a daily basis, we do the following:
   a. The positions on each day for AAPL are multiplied by the corresponding stock's adjusted close price on that day to get the daily investment-amount. The investment-amount for each day is the money we use to buy (spend a positive amount of money) or money we get from selling (spend a negative amount of money) stocks on that day.
   b. Accumulated daily investment-amount from first investment day are calculated and are subtracted from the initial capital to get the remaining cash on each day.
   c. Accumulated positions are multiplied by adjusted close price to get the value of the stock we have on each day.
   d. Remaining cash and value of the stock are added together to get the total asset value.

For instance, if we have 5 continuous trading days and initial capital on the first day is $100000, which

> Daily positions are [100, −200, −100, 0, 200].
> Adjust close prices are [155, 156, 153, 152, 158]
> Daily Investment-amount are [15500, −31200, −15300, 0, 31600]
> Daily remaining cash are [84500, 115700, 131000, 131000, 99400]
> Accumulated positions are [100, −100, −200, −200, 0]
> Daily values of stock are [15500, −15600, −30600, −30400, 0]
> Daily total assets are [100000, 100100, 100400, 100600, 99400]

7. Returns are calculated at the end of last trade, when all positions are closed.

5 Results

After we have simulated the trading using Seeking Alpha's disclosures, we find that returns on 179 stocks were positive, 108 stocks lost money, with 213 stocks stayed neutral for 30 holding days. The stocks stayed neutral because there were no articles about them based our article selection criteria.

The results for all different holding date are shown in Table 2 as follows:

Table 2. Number of stocks made money/lost money/neutral with different holding days

Holding days	Number of stocks made money	Number of stocks lost money	Number of stocks stayed neutral
30	179	108	213
60	195	92	213
90	193	94	213
120	197	90	213
150	198	89	213

We find that, in general, the number of stocks that return positive ROI goes up with an increase in holding period. When the holding days are 180, 71.43% of the traded stocks made money among the stocks discussed is SA and were in the S&P 500 list. Therefore, this preliminary study shows that even the free content on Seeking Alpha is a valuable resource for investors. However, we suggest that looking for the historical performance of the contributors is important before following their recommendation.

Based on our strategy, Table 3 shows the percentage of return.

Table 3. Number of stock in each percentage of return interval.

Percentage of return	Number of stocks
0–10%	181
10%–20%	11
20%–30%	4
30%–100%	5
100%–500%	4

6 Conclusion

Of all the free content available on web and social media platforms, advice on financial investments is most valuable. Understanding this market need, there are a plethora of services for consumers to obtain free information on financial investment. However, acting on faulty financial advice can lead to big financial losses. Therefore, it is critical for us to understand the value of free advice pandered on web and social media platforms.

In this paper, we examine the value of free content provided on an equity review website, Seeking Alpha. Our results demonstrate that this free content is really valuable. 71.43% of the traded stocks made money which were discussed is SA and were in the S&P 500 list.

Future research will investigate the value of paid content over the free content available on these platforms and later compare the value of free/paid content from experts and retail investors.

References

1. Wang, G., Wang, T., Wang, B., Sambasivan, D., Zhang, Z., Zheng, H., Zhao, B.Y.: Crowds on wall street: extracting value from collaborative investing platforms. In: Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work and Social Computing. pp. 17–30. ACM (2015)
2. Gidofalvi, G., Elkan, C.: Using news articles to predict stock price movements. Department of Computer Science and Engineering, University of California, San Diego (2001)
3. Bollen, J., Mao, H., Zeng, X.: Twitter mood predicts the stock market. J. Comput. Sci. **2**, 1–8 (2011). https://doi.org/10.1016/j.jocs.2010.12.007
4. Tumarkin, R., Whitelaw, R.F.: News or noise? Internet postings and stock prices. Financ. Anal. J. **57**, 41–51 (2001). https://doi.org/10.2469/faj.v57.n3.2449
5. Loughran, T., Mcdonald, B.: When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. J. Financ. **66**, 35–65 (2011). https://doi.org/10.1111/j.1540-6261.2010.01625.x
6. Tetlock, P.C.: Giving content to investor sentiment: The role of media in the stock market. J. Financ. **62**, 1139–1168 (2007). https://doi.org/10.1111/j.1540-6261.2007.01232.x
7. Tetlock, P.C., Saar-Tsechansky, M., MacSkassy, S.: More than words: quantifying language to measure firms' fundamentals. J. Financ. **63**, 1437–1467 (2008). https://doi.org/10.1111/j.1540-6261.2008.01362.x
8. Al Nasseri, A., Tucker, A., de Cesare, S.: Big data analysis of StockTwits to predict sentiments in the stock market. In: Džeroski, S., Panov, P., Kocev, D., Todorovski, L. (eds.) DS 2014. LNCS (LNAI), vol. 8777, pp. 13–24. Springer, Cham (2014). https://doi.org/10.1007/978-3-319-11812-3_2
9. Antweiler, W., Frank, M.Z.: Is all that talk just noise? The information content of Internet stock message boards. J. Financ. **59**, 1259–1294 (2004). https://doi.org/10.1111/j.1540-6261.2004.00662.x
10. Chen, H., De, P., Hu, Y.Y.(J)., Hwang, B.-H.B.-H.: Wisdom of crowds: the value of stock opinions transmitted through social media. Rev. Financ. Stud. **27**, hhu001 (2014). https://doi.org/10.1093/rfs/hhu001
11. Das, S.R., Chen, M.Y.: Yahoo! for Amazon: sentiment extraction from small talk on the web. Manage. Sci. **53**, 1375–1388 (2007)

12. Leung, H., Ton, T.: The impact of internet stock message boards on cross-sectional returns of small-capitalization stocks. J. Bank. Financ. **55**, 37–55 (2015). https://doi.org/10.1016/j.jbankfin.2015.01.009
13. Luo, X., Zhang, J., Duan, W.: Social media and firm equity value. Inf. Syst. Res. **24**, 146–163 (2013). https://doi.org/10.1287/isre.1120.0462
14. Dellarocas, C., Awad, N., Zhang, X.: Exploring the value of online reviews to organizations: implications for revenue forecasting and planning. In: ICIS 2004 Proceedings, p. 30 (2004)
15. Lee, M.K.O., Shi, N., Cheung, C.M.K., Lim, K.H., Sia, C.L.: Consumer's decision to shop online: the moderating role of positive informational social influence. Inf. Manag. **48**, 185–191 (2011)
16. Phang, C.W., Zhang, C., Sutanto, J.: The influence of user interaction and participation in social media on the consumption intention of niche products. Inf. Manag. **50**, 661–672 (2013)
17. Eysenbach, G.: Citation advantage of open access articles. PLoS Biol. **4**, e157 (2006)
18. Lawrence, S.: Free online availability substantially increases a paper's impact. Nature **411**, 521 (2001)
19. Gargouri, Y., Hajjem, C., Larivière, V., Gingras, Y., Carr, L., Brody, T., Harnad, S.: Self-selected or mandated, open access increases citation impact for higher quality research. PLoS One **5**, e13636 (2010)
20. Eagly, A.H., Chaiken, S.: The Psychology of Attitudes. Harcourt Brace Jovanovich College Publishers, Orlando (1993)
21. Hovland, C.I., Janis, I.L., Kelley, H.H.: Communication and persuasion; psychological studies of opinion change (1953)
22. McGinnies, E., Ward, C.D.: Better liked than right: trustworthiness and expertise as factors in credibility. Pers. Soc. Psychol. Bull. **6**, 467–472 (1980)
23. Filieri, R.: What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. J. Bus. Res. **68**, 1261–1270 (2015). https://doi.org/10.1016/j.jbusres.2014.11.006
24. Goldenberg, J., Han, S., Lehmann, D.R., Hong, J.W.: The role of hubs in the adoption process. J. Mark. **73**, 1–13 (2009)
25. Tweney, D.: Seeking Alpha: who needs an acquisition when we're doing so well? | VentureBeat | Media | by Dylan Tweney. https://venturebeat.com/2013/10/09/seeking-alpha-acquisition/

Why Do You Need to Buy Virtual Items?: Investigating Factors Influencing Intention to Purchase in Mobile Games

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Abstract. Mobile games have produced almost half of total mobile application revenue. Freemium strategy is commonly used for monetizing methods of mobile games recently. It is getting more attention of game developers to investigate the key factors affecting users' purchase virtual items. Although researchers start to investigate this salient topic, there is still insufficient academic research on the intention to in-app purchase so far. Therefore, the purpose of this study is to investigate the key factors affecting the intention to in-app purchase in freemium mobile games. We evaluate the effects of psychological needs (i.e. autonomy, competence, and relatedness) and promotion (i.e. free item) on the intention to in-app purchase based on key tenets of self-determination theory and self-perception theory. We conduct an online survey and use Partial least squares modeling for our analysis. The results show that autonomy and relatedness needs are positively related to purchase intention while competence need is negatively related to the intention to in-app purchase. Moreover, the direct and meditating effect of free-item promotion are positively related to purchase intention. Interestingly, although competence need is negatively related to purchase intention, free-item experience positively meditates the effect of competence need to purchase intention. In addition, the effect size of purchase experience on purchase intention is the most significant among the suggested factors. This result shows that game companies need to more carefully consider more seriously about the characteristics of paying users. We expect that the findings of this research will deliver significant research insights and actionable implications for researchers as well as practitioners.

Keywords: Freemium mobile games · Partial Least Squares · PLS
Intention to purchase · In-app purchase

1 Introduction

The global market size of the game industry has reached $108.9 billion in 2017, and mobile games solely took over 40% of the market [9]. In this competitive market, mobile game developers eagerly try to attract people to play their games using various

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methods. Freemium ('free' & 'premium') strategy is commonly used for this because many mobile application (app) users want to check the app free at first whether it is worth to use or not, and purchase in-app contents if they are satisfied. However, this strategy does not assure gaining a profit because only a few users purchase in-app contents, normally far below five percentages of total players in mobile games [12]. In this regard, it is important for game developers to figure out the factors affecting in-app purchase in mobile games. Despite starting to shed light on this salient topic [1, 10, 11], there is still insufficient academic research on the intention to in-app purchase. Therefore, we aim to analyze key factors affecting the intention to in-app purchase. Furthermore, we examine the effect of promotion (i.e. free item) on the intention to in-app purchase. Game developers normally offer free items as a sales promotion of in-app contents. For example, they give newcomers welcome-free items for users' easy adaptation or special items to loyal users as a reward. Bawa and Shoemaker [2] present that the effect of free samples on product sales is a blended, which is mixed from acceleration, cannibalization, and expansion. In this sense, we investigate the net effect of items given for free to players whether offering free items cannibalizes or boosts in-app purchase in mobile game context. As such, we aim to answer the following research questions:

- What are the key factors to affect purchase intention in mobile games?
- How do the factors affect purchase intention in mobile games?
- Does offering free-item promote purchase intention in mobile games?

We employ two theories that can help elucidate users' intention to purchase in-app contents: self-determination theory [7] and self-perception theory [3]. The key tenets of self-determination theory are employed to explain the effects of psychological needs on in-app purchase, and self-perception theory concerns the effect of free contents on in-app purchase. We conduct an online survey of players in a leading mobile game and implement structural equation modeling for testing our model. We expect that our findings can deliver significant research insights and actionable implications for researchers and practitioners.

2 Theoretical Backgrounds and Research Hypotheses

2.1 Psychological Needs in Games

Self-determination theory (SDT) categorizes extrinsic and intrinsic factors that either promote or reduce motivation. Extrinsic motivation relates to the performance of a goal-driven activity that leads to achievements or rewards outside of the activity (e.g., salary of work). Intrinsic motivation, in contrast, focuses on the pleasure of being involved in an activity. Intrinsic motivation can be encouraged by three basic needs—autonomy, competence, and relatedness. Autonomy refers to being able fully to control one's actions and feeling volitional. Competence refers to feeling effective and capable challenged. Lastly, relatedness refers to the feeling meaningful connection to others. Satisfaction of these three needs is important in intrinsic motivation [7].

In the game context, intrinsic motivation is essential. Obviously, players play games because they consider games are enjoyable and amusable. Intrinsic motivation can be promoted by satisfying three psychological needs [13]. For example, interesting options in the game can boost the sense of autonomy of players. The needs of competence can be satisfied by elaborated specific, difficult but achievable goals. Lastly, players can feel relatedness by interacting with other players. In addition, game developers offer various types of virtual items to entice users to keep playing by effectively reducing users' boredom [6, 15]. Accordingly, if players feel deficient in autonomy, competence, and relatedness needs when they think the game is enjoyable, they are willing to purchase in-app contents to fulfill them. Therefore, the hypotheses are formulated as follows:

- Hypothesis 1: The autonomy need is positively related to intention to purchase in a mobile game.
- Hypothesis 2: The competence need is positively related to intention to purchase in a mobile game.
- Hypothesis 3: The relatedness need is positively related to intention to purchase in a mobile game.

2.2 Self-perception in Games

Self-perception theory explains the process of developing self-perceptions about one's behavior [3]. According to this theory, customers can realize the value and influence of product after using it. Furthermore, the customer may be considered as a potential tester once accepting free-sample product, and (s)he can be counted as a potential buyer when the purchase opportunity is given. Once the customer accepts to receive sample products first, (s)he is more likely to accept purchase requests later.

The process of making self-perception can be applied well to game context since in-app contents are a kind of experience goods [14]. While customers can know the value of information goods when the information is carried, they cannot realize the value of experience goods until consumed. In this sense, players cannot know the usefulness of in-app contents unless they use. They can build self-perception of items through consuming free items as well as purchased items. As such, we hypothesize:

- Hypothesis 4: Purchase experience is positively related to intention to purchase in a mobile game.
- Hypothesis 5: Free-item experience is positively related to intention to purchase in a mobile game.

Game developers normally offer free items as one of promotion strategies. They provide free items to make players realize what they need exactly. Regarding autonomy needs, the developers offer various options through free items, which players can choose such as trial costumes, trial hint items, etc. In terms of competence needs, the developers give to newcomers welcome-free items for helping easy adaptation. Lastly, regarding relatedness needs, the developers encourage players' social interaction by providing free items. For example, players can get free items after introducing the game to their friends. Accordingly, this leads us to formulate the following hypotheses:

- Hypothesis 6: The autonomy need is positively related to free-item experience in a mobile game.
- Hypothesis 7: The competence need is positively related to free-item experience in a mobile game.
- Hypothesis 8: The relatedness need is positively related to free-item experience in a mobile game.

Therefore, our conceptual model is presented in Fig. 1.

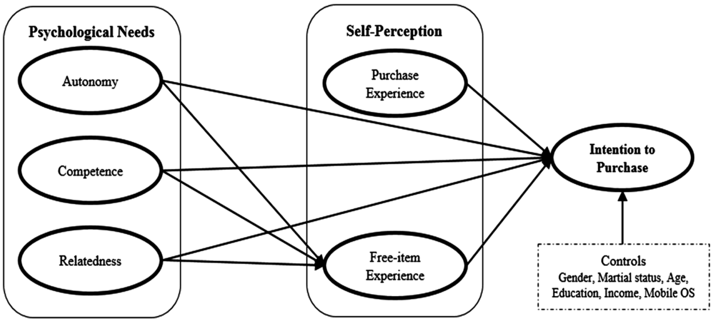

Fig. 1. Conceptual model

3 Method

Our research model is tested with online survey data from a leading freemium mobile game in Korea. This game is a kind of simple puzzle game. Players can move to a next stage after finding all pairs of the same patterns during a certain time. We obtain 4,556 qualified responses after deleting 229 invalid responses. Table 1 shows the demographic information about the respondents.

Partial least squares (PLS) modeling is conducted in SmartPLS 3.0 to evaluate the proposed model and hypothesized relationships among constructs. We decide to use PLS because of our data characteristic (i.e. our hypothesized relationships are complicated and few bases have been established) and specific advantages of PLS (i.e. minimal restrictions on measurement scales, sample distribution, and sample size).

The adequacy of the measurement model is examined based on the criteria of reliability and validity. Reliability is tested based on the composite reliability (CR) values. All values of CR are above 0.804. The convergent validity of the scales is evaluated by criteria [5, 8]. All of the items indicate a loading higher than 0.7 on their respective constructs, and all of the AVEs range from 0.507 to 0.861. This result shows that both criteria for convergent validity are acceptable and the measurement items converge on the same latent construct. To examine discriminant validity, we investigate the values of the cross-factor loadings and the square root of the AVE. Based on these test, the research model has the reliability and validity of the constructs.

Table 1. Demographic information about the respondents (N = 4,556)

Measure	Items	Frequency	Percent
Gender	Male	639	14
	Female	3917	86
Marital status	Single	2518	55.3
	Married	2038	44.7
Age	<19	91	2
	19–24	902	19.8
	25–29	846	18.6
	30–35	1279	28.1
	35<	1438	31.6
Education	High school ↓	710	15.6
	University ↓	2920	64.1
	Graduate school ↓	926	20.3
Income (per month, KRW)	<1,000,000	1557	34.2
	1,000,000–1,999,999	1242	27.3
	2,000,000–2,999,999	1012	22.2
	3,000,000–3,999,999	394	8.6
	4,000,000–4,999,999	166	3.6
	5,000,000–9,999,999	136	3
	9,999,999 <	49	1.1
Mobile OS	Android	3005	66.0
	iOS	1503	33.0
	Other	48	1.1

4 Result and Discussion

Path coefficients and R^2 values are obtained by running the PLS algorithm to assess the predictive performance of the structural model. The model accounts for 1.8% of the variance in free-item experience, and the model accounts for 30.8% of the variance in general purchase intention of players. Thus, over 30% of the intention to in-app purchase in mobile game is explained by suggested factors: psychological needs and self-perception. In addition, the results present strong support for all relationships of the research model in Fig. 2.

In this study, we observe several significant findings. First, in terms of psychological needs, the needs of autonomy and relatedness are positively related to intention to in-app purchase. This result explains that players who have want more options to play and more friends in game are likely to purchase in-app contents. However, interestingly, competence need is negatively related to intention to in-app purchase. This result shows that players who want to get a high score or move to the next stage in a short time with less trial are not likely to purchase in-app contents. This implies that the players may want to obtain their achievement in the game without additional cost. Furthermore, the mediating effects of free-item experience with psychological needs are

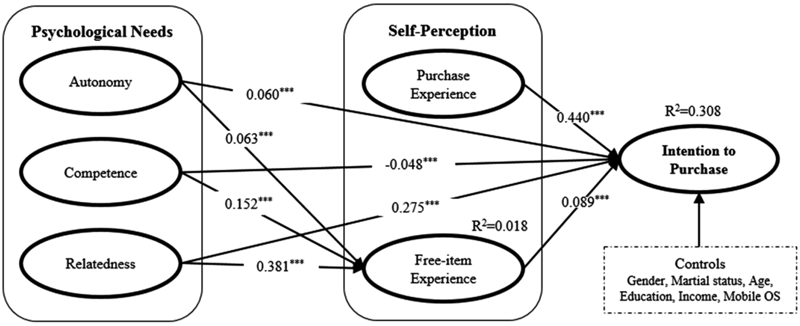

Fig. 2. The research model with empirical results

positively related to intention to in-app purchase. While competence need is negatively related to purchase intention, free-item experience positively meditates the effect of competence need to purchase intention. Therefore, for practical implications, our results suggest that the promotion of offering free items is effective to increase intention to in-app purchase for players with autonomy, competence and relatedness needs. Furthermore, game developers need to consider the importance of paying users since the effect size of purchase experience on purchase intention is the biggest among suggested factors. For free users, it would be effective aggressively to offer free items for shaping self-perception.

5 Conclusion and Research Plan

The purpose of this study is to examine key factors affecting in-app purchase and examines the effect of free-item promotion. We explain the effects of psychological needs on in-app purchase with the key tenets of self-determination theory and the effect of free contents on in-app purchase deliberated by self-perception perspective. As a result, we find that psychological needs of autonomy and relatedness are positively related to in-app purchase, while competence need is negatively related to in-app purchase. Moreover, free-item promotion is positively related to in-app purchase.

Although useful implications of our results, the study still requires further refinements. First, this study conducts online survey of players in a suggested game only, so it is hard to figure out the effect differences of the key factors with other game genre. In addition, as with most online surveys, participation of our survey is based on self-selection and the participants are not expected to be representative of all mobile gamers. Furthermore, we provide free items to players who participate in our survey as a reward so it can be possible to exaggerate the propensity of players who want to get free items. Therefore, it can be another research opportunity to conduct additional analysis by comparing our result to secondary data. Consequently, our research will be strengthened and elaborated after considering the above-mentioned limitations.

References

1. Animesh, A., Pinsonneault, A., Yang, S.B., Oh, W.: An Odyssey into virtual worlds: exploring the impacts of technological and spatial environments on intention to purchase virtual products. MIS Q. **35**(3), 789–810 (2011)
2. Bawa, K., Shoemaker, R.: The effects of free sample promotions on incremental brand sales. Mark. Sci. **23**(3), 345–363 (2004)
3. Bem, D.: Self-perception theory. In: Berkowitz, L. (ed.) Advances in Experimental Social Psychology. Academic Press, New York (1972)
4. Chin, W.W.: Issue and opinions on structural equation modeling. MIS Q. **22**(1), 7–16 (2003)
5. Chiu, C.M., Hsu, M.H., Lai, H., Chang, C.M.: Re-examining the influence of trust on online repeat purchase intention: the moderating role of habit and its antecedents. Decis. Support Syst. **53**(4), 835–845 (2012)
6. Cotton, B.: Social Game Design: Monetization Methods and Mechanics. Morgan Kauffman, Burlington (2011)
7. Deci, E.L., Ryan, R.M.: Intrinsic Motivation and Self-determination in Human Behavior. Plenum, New York (1985)
8. Fornell, C., Larcker, D.F.: Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. **18**, 39–50 (1981)
9. Global games market report. https://newzoo.com/solutions/standard/market-forecasts/global-games-market-report
10. Guo, Y., Barnes, S.J.: Explaining purchasing behavior within World of Warcraft. J. Comput. Inf. Syst. **52**(3), 18–30 (2012)
11. Hamari, J.: Why do people buy virtual goods? Attitude toward virtual good purchases versus game enjoyment. Int. J. Inf. Manage. **35**(3), 299–308 (2015)
12. Monetization report. https://www.swrve.com/images/uploads/whitepapers/swrve-monetization-report-2016.pdf
13. Uysal, A., Yildirim, I.G.: Self-determination theory in digital games. In: Bostan, B. (ed.) Gamer Psychology and Behavior. Springer, Switzerland (2016)
14. Wang, C.A., Zhang, X.M.: Sampling of information goods. Decis. Support Syst. **48**(1), 14–22 (2009)
15. Zarnekow, N.H.R.: Purchasing behavior in free to play games: concepts and empirical validation. In: Proceedings of the 48th Hawaii International Conference on System Sciences (2015)

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A Theory of Information Biases on Healthcare Platforms

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Abstract. In this paper, we present a theory of information biases generated by online physicians/doctors who work on healthcare platforms. We find that the private information that originates from the expertise of the physicians and their professional investigations on patients' reports/messages would induce a persistent bias on diagnostic reports. This information bias would further influence the demand of online healthcare services in two ways. First, the more skeptical the rational patients are towards the potentially biased diagnostic information, the less likely their decision would rely on the diagnostic reports generated by the physicians. Second, the information bias would make certain types of diagnosis (medical reports) come up more often than others. We also find that the private information gives online physicians more incentive to bias their reports if their return of career concern depends on the reputation of being providers of accurate diagnostic reports. For the healthcare platform, we find that the bias can be reduced by restricting the discretion allowed to physicians, but the platform's profit would be increased if more bias is allowed. We also present a variety of testable predictions related to the registration fee charged by healthcare platforms.

Keywords: Healthcare platform · Information bias · Information provider
Online physicians · Asymmetric information · Bayesian update
Perfect bayesian equilibrium

1 Introduction

In the last few years, healthcare industry has also been influenced by the powerful Internet. This industry today has experienced numerous challenges, and the most important one is the rising cost of healthcare. According to CMS (Centers for Medicare & Medicaid Services) in 2016, the United States spends $3.4 trillion annually on healthcare which is almost 17% of the country's GDP, and is currently around twice the OECD (Organization for Economic Co-operation and Development) per capita average (Einav and Levin 2015). People argue that the lack of effective coordination mechanism and information sharing could be the key factors to raise the cost. Therefore, the Internet and health information technology (HIT) which are treated as effective ways to address these challenges have been integrated to the healthcare sector. Previous

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researches notice that the adoption of the Internet and HIT can reduce medical errors, lower healthcare costs, and improve overall quality (e.g., Ayal and Seidman 2009; Jack and Powers 2004; Khoumbati et al. 2006; Peng et al. 2014). Meanwhile, on the supply side, companies all over the world are trying to create new online healthcare platforms or telemedicine, such as Amwell and Zocdoc in the United States, Hao Dai Fu ("good doctor" in Chinese) in mainland China, and Practo Health in India, to more effectively connect patients and physicians/doctors so as to reduce the huge cost in healthcare industry.

However, on the demand side, patients have concerns about the credibility and quality of online healthcare platforms as well as privacy protection when using these platforms (Kraschnewski and Gabbay 2013; Zahedi et al. 2016). Meanwhile, anecdotal evidence also tells us that online healthcare platforms have the same issue as other online platform, i.e., information asymmetry, which induces market inefficiency. For instance, according to Oliver Kharraz, founder of Zocdoc (online physician finder and appointment booker), the lack of trust has hindered physician ratings. Although we have not obtained any direct empirical evidence to support the conjecture of the existence of information asymmetry, some studies[1] have noticed that patients consider that online review sites are "very important" or "somewhat important" for picking a physician. These studies imply that patients are skeptical towards the diagnosis/ information provided by online physicians who work on healthcare platforms. In our view, this skepticism is generated by information asymmetry between patients and online physicians. Otherwise, patients would not rely so much on the online reviews to choose their online physicians.

Therefore, in this paper, we develop a theoretical model to study healthcare platform's equilibrium discretion strategy (i.e., strategy that grants freedom and flexibility to online physicians to produce diagnostic reports) and online physicians' reporting strategy when there is information asymmetry between patients and online physicians. We start from a simple assumption: Both the healthcare platform and physicians want to build a reputation as provider of accurate information. A good reputation would help the healthcare platform to expand the market demand for their services, i.e., attract more patients to register and purchase their services. Physicians who work for the platform would use this reputation for their future career concerns. If the quality of diagnosis information is difficult to be observed or verified, then patients' beliefs about quality of diagnosis information will be largely based on the prior[2], i.e., initial belief, on the platform or physicians. The platform and physicians will then both have an incentive to alter the diagnostic report in whatever ways that will be most likely to maximize their profit and improve their reputation in the market.

Our analysis derives several notable results. Our first main result shows that the platform will tend to set up discretion to allow physicians to distort diagnostic information to make it conform with patients' prior. This is because, an inaccurate or noisy

[1] For instance, a study (Hanauer et al. 2014) surveys 2,000 adults in the U.S. and tries to find the importance of online physician reviews.

[2] In reality, this belief could be formed in many different ways. For instance, patients might form this belief based on the online review on physicians or platforms.

health description is more likely to generate a diagnostic report that contradicts the truth. A patient who has a strong prior belief about his true health state will therefore expect inaccurate diagnostic reports, more often than accurate ones, to contradict that belief, i.e., patients are skeptical towards reports provided by the platform or physicians. Suppose, for example, a physician reports that a patient who is 31 years old has a very high risk to get type 2 diabetes. However, if the patient believes this to be highly unlikely, he will rationally infer that this physician probably has poor expertise in his field. A platform and physicians who concern about their reputation for accuracy and profit will therefore tolerate a biased diagnostic report to be consistent with patients' prior, even if they believe that the evidence is true. In other words, tolerating biases on diagnostic reports is consistent with profit maximization in equilibrium.

However, if they do not value the rewards of market reputation, or the rewards are too small, then the platform would not grant any freedom to the physicians' diagnostic reports, i.e., no biased reports would be generated in equilibrium. The intuition is that, when the future reward is small, the physicians' future benefit from being a good physician would be small. Therefore, the platform has to pay more to hire physicians, i.e., the platform's profit would be decreased. In optimal, we find that the platform's registration fee for patients is decreasing with the granted discretion, then the platform has an incentive to decrease the discretion so as to increase the registration fee which would further cancel out the increased cost from hiring physicians.

Our second main result is that, when the platform tolerates biases, it has to lower its registration fee, i.e., the registration fee and biases are negatively correlated. This is because patients' skepticism about the possible biases on the diagnostic reports induces the healthcare platform to set a lower price for its advanced services, and a profit-maximizing healthcare platform would tolerate biases when it gains more on the supply side, e.g., lower registration fee, than it loses on the demand side, i.e., market reduction caused by the equilibrium biased diagnostic reports. In other words, the biased reports in equilibrium decrease the market demand on the platform's services. To cancel out the potential market reduction caused by biased reports, the platform has to lower the registration fee. We also find that, the registration fee would be decreasing with patients' initial belief. This is because strong skepticism on the demand side (i.e., patients) would lower the market demand. Therefore, in order to maximize profit, the platform has to lower the registration fee to attract these skeptical patients.

Thirdly, we present a set of testable predictions (i.e., equilibrium results) on the optimal registration fee charged by the platform:

(1) It is decreasing with the platform's marginal revenue from advertising. This is because, an increase in the marginal revenue of advertising gives the platform an incentive to increase demand, which further induces the platform to decrease the registration fee.
(2) It is increasing with patients' potential loss from a bad health condition and patients' marginal cost of taking a precaution. This is because, a high loss from a bad health condition gives patients an incentive to take advanced consultation to get more information on whether a precaution or other actions should be taken. This makes the diagnostic reports from online physicians more valuable. Thus the platform would charge more from these patients to maximize profit.

(3) It is increasing with physicians' expertise and their wage from the platform. First, more sophisticated physicians usually can identify the true state of patients' health condition more often than other physicians. These physicians are more demanded than others. Therefore, a platform with more sophisticated physicians would charge more. Second, when physicians' wage increases, the platform's cost would increase. Thus, to offset the increased cost, the platform would charge more from patients who intend to take advanced consultation.
(4) It is increasing with patients' potential loss from a bad health condition and patients' marginal cost of taking a precaution. This is because, when the cost of taking a precaution is high, a physician's report would be more valuable to patients. Thus the platform would charge more.

Our fourth set of results tells us that, the platform's optimal profit is increasing with patients' marginal cost of taking a precaution and decreasing with patients' prior of being in a bad health condition. This is because, when the average marginal cost of taking a precaution increases, the diagnostic report would be more valuable even if it is biased; therefore, the registration fee and demand would increase, and the profit would also increase. However, when a patient initially believes that he is in a bad health condition with high probability, the value of getting a diagnostic report from a physician decreases, which further reduces both the registration fee and market demand. Thus the total profit would decrease accordingly.

The analysis of revenue from advertising derives our last result. The profit is decreasing with patients' potential loss from a bad health condition when the marginal revenue from advertising is large; and is increasing with the loss when the marginal revenue from advertising is small. This is because, previous result tells us that, high loss from a bad health condition would induce a high registration fee, which would further reduce the market demand. When the marginal revenue from advertising is large, the reduced market demand would reduce revenue from advertising. Then the total profit would decrease accordingly. However, when the marginal revenue from advertising is small, the loss from reduced advertising revenue is smaller than the increased revenue from high price. Then the total profit would increase.

2 Literature Review

The growing importance of healthcare platforms has recently attracted academic attention. However, there has been a significant lack of relevant research on healthcare platform *per se*. To the best of our knowledge, our research is the first analytical paper to analyze the market incentives of healthcare platforms. Our research is generally related to three streams of literature.

First, our study is related to the literature of healthcare information technology (HIT) (e.g., Agarwal et al. 2010; Bhargava and Mishra 2014; Goh et al. 2011; Menon et al. 2000; Miller and Tucker 2013). Many researchers in this field studied the impact of digitization of healthcare industry. For instance, Anderson and Agarwal (2011) studied under what circumstances patients will be willing to disclose identified personal health information and allow it to be digitized. Aron et al. (2011) examined how incremental automation over time and across multiple wards impacts the rate of medical errors. Kohli and Tan (2016) investigated how Electronic health records (EHRs) facilitate the integration of patients' health history for their treatment.

In addition to the impact of digitization of healthcare industry, the impact of the Internet on healthcare has also attracted significant attention recently. For instance, Yan and Tan (2014) investigated whether social support exchanged in an online healthcare community benefits patients' mental health. Yan et al. (2015) explored the driving forces to patients' online social network formation and evolution.

However, most of these previous studies have either focused on factors related to the supply side of the healthcare market, such as the impact of the adoption of digital health records on healthcare provider (e.g., Ozdemir et al. 2011), or the demand side of healthcare market, such as the impact of using telemedicine on patients (e.g., Rajan et al. 2013). They have overlooked the market of healthcare platforms itself. Thus, our research differs from prior literature by investigating how market incentives affect healthcare platforms and online physicians' actions. Our model can be the building blocks for future research on the healthcare platform market.

Second, our study is related to the growing literature on peer-to-peer markets. The goal of healthcare platforms is to facilitate efficient interactions between a large number of patients and physicians. This requires solving several problems which are typical in peer-to-peer markets. The most important one is to lower the transaction cost, such as the cost induced by information asymmetry between patients and online physicians. A recent literature has asked whether intermediaries, i.e., online platforms, have an incentive to present search results in ways that lower the transaction cost so as to create maximal benefits for users. These studies point out that platform incentives may not align fully with consumers, especially if platforms can obtain higher revenue if a buyer chooses a special seller (Armstrong and Zhou 2011; Eliaz and Spiegler 2011; Hagiu and Jullien 2011). This can happen if certain sellers pay higher fees, or are vertically integrated with the platform (Cornière and Taylor 2014). Our paper has the similar finding that, the intermediary, i.e., healthcare platform, has an incentive to give online physicians discretion to bias the diagnostic reports which may not be the best for patients.

Third, our work is also closely related to the economics literature on herding on the priors. This literature studies how an agent's actions depend on prior beliefs of factors that may determine the agent's utility. Prendergast (1993) found that this dependence could drive workers to bias the reports to match the information that managers have received, and valuable information could be lost in equilibrium. Moreover, Brandenburger and Polak (1996) studied how shareholders' priors affect managers' decisions which may affect stock prices. In contrast to this literature, the interaction we model here in turn generates an inefficient equilibrium, and biased information could be sustained by rational healthcare platforms and online physicians.

3 Theoretical Issues: Information in the Market of Healthcare Platforms

The most important aspect that our model considers is the information asymmetry[3] in the market of healthcare platforms. In our view, the market of healthcare platforms has private information about:

(1) The true health condition of patients who register on the platform, especially for patients who have chronic diseases[4], such as type 2 diabetes.
(2) The ability or the expertise of the physicians who register on the platform.
(3) The reporting strategy of physicians when they generate diagnostic reports.

Let us consider a world with two states, and each state represents the true health condition of each patient. Therefore, if patients value their own health condition, their utility would depend on these states. Meanwhile, patients also have information about which state of the world will be realized more likely if they do not take any actions. If patients honestly report their health condition to the physicians, then physicians would also have private information about the world. In general, physicians' information would be more reliable than that from patients, and the accuracy of the information would depend on physicians' ability or expertise, and how they report it. For instance, given a chronic disease, e.g., type 2 diabetes, a senior physician usually has more knowledge about the possible complications of this disease than a junior physician who is new in the career, especially for chronic diseases. A patient may believe that he is going to die if a surgery is not taken; however, a senior physician's experience might indicate otherwise.

In our model, we assume that information provided by physicians is not verifiable. In other words, information provided by physicians cannot be credibly revealed to the patients[5]. We still use type 2 diabetes as our example to demonstrate the idea. A patient's high blood level could be triggered by several causes such as unhealthy diet. However, at the beginning, the online physician cannot convince the patient that his problem is caused by unhealthy diet. The physician could spend more time with

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[3] The existence of information asymmetry between patients and physicians has been recognized in the economics literature for a long time. For instance in Arrow (1963), he points out that: "…physician is using his knowledge to the best advantage… the patient does not, at least in his belief, know as much as the physician…"

[4] Previous research, e.g., Jemal et al. (2005), has noticed that chronic diseases are a major factor which causes mortality and disability in the United States. Studies (e.g., Thorpe et al. 2004) also find that chronic diseases might be the main part of the 18% of the GDP in the United States which is the total healthcare spending in the United States. According to Johns Hopkins University (2004), about 140 million Americans have at least one chronic condition, and an estimated value indicates that nearly 50% of Americans will have at least one by 2030.

[5] In economics, especially in the literature of contract theory, e.g., Tirole (1986), this information is also called soft information which is different from the definition of soft information in the IS literature.

follow-up tests to provide further evidence to convince the patient, but the result of such further effort would be subject to the initial belief (prior) of the patient.

This assumption could induce physicians on the platform to choose the following equilibrium predictions. If an online physician's experience tells him that the patient's true health condition is not consistent with the patient's belief, the physician could truthfully report the observed information or misreport it by following patient's beliefs despite what he observes. If the observed information is consistent with patient's belief, the physician could truthfully report the information to follow patient's belief or go against it by misreporting the information.

Furthermore, the feature of non-verifiability of information and the benefit from advanced services give online physicians incentives to bias information, i.e., the moral hazard problem, in another dimension, i.e., encourage patients to purchase advanced services using the diagnostic reports. For instance, after reading a patient's health description, an online physician could generate a report:

> *"…The patient is experiencing high risk to [early stage of] type 2 diabetes, and we suggest the patient take an advanced service from our online platform to do a follow-up treatment/testing or get further physical examination from the recommended medical center…"*

From this report, it is hard for patients or any other professional medical centers to verify if the information provided here represents the truth. Patients usually update their beliefs on their true heath condition based on this report and decide whether to take further actions, such as an advanced service from the platform, which would be beneficial to online physicians and the platform.

All these specifications on the information structure on the market reflect the fact that, the uncertainty on the market of healthcare platforms comes from:

(1) the system (the state of patients' true health condition is not realized);
(2) online physicians' private expertise (adverse selection);
(3) the platform's hidden action during information reporting (moral hazard).

Noteworthy, we also emphasize that information is the key to drive the equilibrium actions of patients, online physicians and the healthcare platform.

4 The Model

Let us consider a market with a continuum of patients, one online healthcare platform, and a finite number of physicians[6] who work on the healthcare platform. A Patient may use the healthcare platform to get health service through consulting with an online physician. The patient may choose a costly action, which will be specified later, after

[6] This setup induces that the number of patients is larger than the number of physicians in the market. We use this setup to capture the fact that physician is scare resource in the market.

consulting with the physician. In the consultation, patients will honestly[7] send detailed information[8] (messages) on their health condition to online physicians.

The patients are assumed to be rational in the sense that:

(1) They update their beliefs on the health condition of themselves by the Bayes' rule after observing diagnostic reports from a physician.
(2) They optimally choose their actions given the beliefs. Patients who register for the advanced service will base their actions on the diagnostic report, and those who do not register will base their actions on their prior information.

The platform sets up price or registration fee for advanced consultation[9] and discretion[10] for physicians to maximize the profit. Here, we consider the discretion as a part of the reputation of the platform. We also allow the platform to get profit from advertising which is positively related to the number of patients who register for advanced consultation. For physicians, they could observe private information on each patient's true health condition by analyzing the message provided by them. This private information and the discretion granted by the online platform provide an opportunity to physicians to bias the diagnostic report.

We assume that all physicians who work on the same platform are homogeneous[11] in terms of their expertise. Therefore, each patient gets the same service across all physicians from the platform. We also assume that the diagnostic reports generated by physicians are demanded by patients and can be used by the patients for their further decisions. This assumption induces that patients will endogenously become informed on their true health condition by registering on the healthcare platform or remain uninformed by not registering.

We use Fig. 1 to illustrate the interactions among patients, online physicians, and the healthcare platform.

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[7] The goal of this paper is to analyze the bias generated by online healthcare platforms, so we assume that patients always truthfully report information about their health condition to physicians. This assumption would simplify our analysis but does not influence the main results.

[8] For instance, patients and physicians could communicate through online chatting functions provided by the platform (see Hao Dai Fu in the Chinese market as an example). However in this paper, we do not model the details of this communication process, but simply assume that, at the end of a communication, an honest message will always be sent from a patient to a physician.

[9] In reality, there might be two consultations across different platforms. In the first one, which is usually free, patients communicate with online physicians to get general information about each other. If a patient wants to have a further and more professional consultation, he needs to make a payment. The amount of payment is usually determined by the platform. In this model, we do not consider the difference between the two consultations.

[10] Here, we borrow the word "discretion" from the economics literature, e.g., Kydland and Prescott (1977), to describe the freedom or flexibility of online physicians' actions. More discretion implies that online physicians face lower restriction on the contents of diagnostic reports. In a very extreme case (i.e., highest discretion), physicians could write whatever they want to write. Less discretion implies higher restriction on the contents of the diagnostic reports. For instance, the platform may put strong moral standards on physicians' actions and does not allow them to write any information which does not consistent with the verifiable evidence.

[11] We could extend this to a setting with heterogeneous physicians. However, main results still hold and no new insights would be generated through this complicated extension.

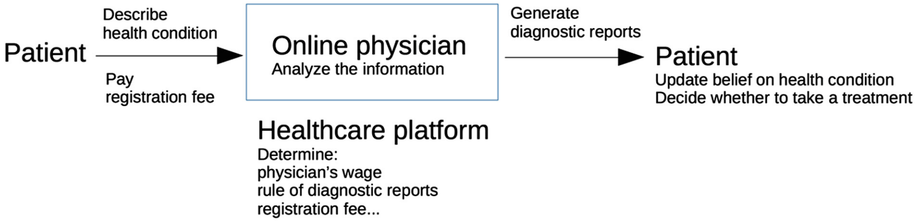

Fig. 1. Interactions among Patients, Online Physicians, and the Healthcare Platform

4.1 Information Structure

We assume that the true health condition of each patient is described by a binary state $\omega \in \Omega = \{\mathrm{B,G}\}$, where B is bad state indicating that a patient is in a bad health condition and would have some loss if no action is taken, and G is a good state indicating that the patient is healthy or any other conditions which would not induce any loss if no action is taken. The prior distribution of the state is Prob(B) = $p_0 \in (0, 1)$. Physicians from the online healthcare platform can use their expertise to analyze the information reported by patients and obtain information about the true state. After the analysis, the physician privately observes a noisy signal $s \in \{\beta, \phi\}$ which is related to the true state. The relation between the signal and the true state is described by the following probability distribution:

$\mathrm{Prob}(s = \beta|\omega = \mathrm{B}) = q \in (0, 1)$ and $\mathrm{Prob}(s = \beta|\omega = \mathrm{G}) = 0$.

Here, we explain the parameter q as a measure of the average level of physicians' expertise on this healthcare platform[12]. Higher q indicates that, on average, physicians are more sophisticated in their fields. This information structure implicitly assume that: If a patient is healthy, the physician would never observe a signal indicating that the patient is in a bad health condition. This assumption is used to simplify the analysis[13]. We also assume that, for the physicians, the cost of diagnosis (i.e., the analysis on the information provided patients) is normalized to zero.

Based on the s, the physician generates a diagnostic report to the patient. The strategy of the physician is a diagnostic report conditional on the observed signal. In general, we would consider a mixed strategy, i.e.,

$$\sigma(s) = \mathrm{Prob}(r = \beta|s) \in (0, 1)$$

where $r \in \{\beta, \phi\}$ is the action (i.e., a report) of a physician. We assume that if the diagnosis shows that the patient is in a bad condition, the physician would always tells

[12] Since we assume that physicians are homogeneous in terms of their expertise, we can also use q to measure a representative physician's expertise.

[13] In general, we could consider a more general case under which, with positive probability, the physicians could observe a signal indicating that the patient is in a bad condition. This generalization would only complicate our analysis, but would not affect the main results and no new insights would be generated.

the truth, i.e., we would focus on the equilibrium under which $\sigma(\beta) = 1$[14]. To simplify the notation, we let $\sigma \equiv \sigma(\phi)$ This means that, given that a physician observes $s = \phi$, he truthfully reports $r = \phi$ with probability $1 - \sigma$, and with probability σ, he biases the report as $r = \beta$. As will be shown below, in equilibrium, physicians will choose to fully exercise the discretion granted by the platform.

4.2 Patients' Preference

In this paper, we assume that patients have a demand for diagnostic reports that can improve their health condition or make them believe that they are healthy. We assume that, each patient has a utility function[15] as follow:

$$u(d|\mathrm{B}) = b(d-1) - \alpha[b(d-1)^2 - cdb,$$

if he has a bad health condition and chooses an action $d \in \{0, 1\}$. Here $\alpha \in [0, A]$ is a measure of patients' risk aversion; and $b > 0$ is the loss of a patient, if he has a bad health condition and does not take any treatment. If he is healthy, then there is no loss. We use $d \in \{0, 1\}$ to indicate the patient's action, where 0 means that no treatment is taken, and 1 means that a treatment is taken. If he takes a treatment, he has to pay a total cost of cb, where $c \in [1, 1 + Ab)$[16] is the marginal cost of taking a treatment. Here, we also assume that if the patient takes a treatment, the total cost would depend on his health condition, which is modeled to be cb. High value of b indicates serious health issue which requires high cost.

Under this preference, the decision on whether to take a treatment is not necessarily connected with whether to register for advanced services on the healthcare platform. This means that, if patients do not engage into the communication with online physicians, they still could choose whether to take a treatment based on their current information. The key difference between a treatment after observing a diagnostic report and a treatment without it is whether to pay the registration fee to the platform.

We assume that patients are differentiated by the risk aversion parameter α, which is uniformly distributed on $[0, A]$. Here, patients with high risk aversion are more willing to take a treatment, whereas patients with low risk aversion are more willing to bear the risk of getting a worse health condition. For instance, the bad state could be that a patient is getting type 2 diabetes, a high risk aversion patient would be willing to take a treatment and a low risk aversion patient would not.

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[14] It can be proved that this is an equilibrium strategy for the physician. If we use the more general setup here, we have to deal with the issue of multiple equilibria which only complicates the analysis with no new insights.

[15] To be more precise, the utility defined here is the utility before paying the registration fee F.

[16] This assumption is purely for technical reason. If c > 1 + Ab, then no patient would act even if he/she is in a bad condition. If c < 1, each patient would act no matter what report is generated, which means there is no demand for health reports.

4.3 Timing

The sequence of interactions in the model is as follow:

(1) Nature determines the state of the world, i.e., the true health condition of patients.
(2) The online healthcare platform sets up the discretion or the standard, σ, to online physicians, and hire physicians from the labor market by paying a wage $w > 0$ to each of them.
(3) Physicians choose to accept or reject the offer.
(4) The online health platform sets up a price F for advanced consultation which is publicly observed.
(5) If patients decide to pay and engage in the advanced consultation, they honestly send information about their health condition to physicians.
(6) Physicians privately observe a signal $s \in \{\beta, \phi\}$ by analyzing the information provided by patients and strategically generate a diagnostic report $r \in \{\beta, \phi\}$ to each patient;
(7) After observing the reports, patients update beliefs and choose further decisions: Whether to take a treatment or not.

We use perfect Bayesian equilibrium to solve the game.

5 Main Results

Due to the limit of space, we only list main results in this section.

Proposition 1:

(1) $p_\beta > p_0$ if $\sigma \in (0, 1)$, and $p_\beta = 1$ if $\sigma = 0$.
(2) p_β is decreasing with σ and increasing with q.
(3) P_ϕ is decreasing with q and $p_\phi < p_0$.
(4) Prob$(r = \beta)$ is increasing with σ.

Proposition 2: Patients would always choose $d = 0$ if $\alpha \in [0, \alpha_L]$, and always choose $d = 1$ if $\alpha \in [\alpha_H, A]$, no matter whether or not they pay for advanced consultation to get diagnostic reports from physicians.

Proposition 3:

(1) Patients would pay for advanced consultation if $\alpha \in (\overline{\alpha}_L, \overline{\alpha}_H)$.
(2) The market demand for advanced consultation is decreasing with the fee charged by the platform, and is decreasing with the bias.
(3) Patients' expected surplus is increasing with q and decreasing with σ. Meanwhile, the expected surplus is increasing with α when $\alpha \in (\overline{\alpha}_L, \alpha_M)$ and decreasing with α when $\alpha \in (\alpha_M, \overline{\alpha}_H)$.

Proposition 4: The optimal fee charged by the platform for advanced consultation, F^*, is

(1) decreasing with the discretion σ, patients' initial belief p_0, and the marginal revenue from advertising m; and
(2) increasing with patients' potential loss from a bad health condition b, patients' marginal cost of taking a precaution c, physicians' expertise q, and physicians' wage from the platform w.

Proposition 5: The platform's optimal profit is increasing with patients' marginal cost of taking a precaution C and decreasing with patients' prior of being in a bad health condition. Meanwhile, it is decreasing with patients' potential loss from a bad health condition b when the marginal revenue from advertising m is large; and is increasing with the loss when the marginal revenue from advertising m is small.

Proposition 6: The optimal contract offered by the platform, $(w, \overline{\sigma})$, to online physicians has the following properties:

1) The optimal discretion would be $\overline{\sigma}^* = 0$ if R is small or $\overline{\sigma}^* \in (0, \overline{\sigma}^U)$ if R is large.
(2) When q > 3/4 and the revenue from advertising is large, the optimal discretion would be $\overline{\sigma}^* = 0$.
(3) In optimal, online physicians would fully exercise the discretion granted by the platform, i.e.,$\sigma^* = \overline{\sigma}^*$.
(4) The optimal wage w^* is decreasing with the discretion allowed by the platform.

6 Policy Implications

In this paper, we argue that the following factors would play key roles in determining the optimal diagnostic reporting strategy of the healthcare platform and physicians, including the non-verifiability of diagnostic reports, patients' initial belief on their health condition and the future rewards of being a good platform or physician. We next highlight two policy implications based on our equilibrium results.

First, the inefficiency, i.e., biased diagnostic report, of the market of healthcare platforms is caused by the non-verifiability of the diagnostic reports generated by physicians. This is mainly caused by the expertise of physicians which has been noticed by both researchers (e.g., Arrow 1963) and the media (e.g., The New York Times 2010) for a long time. The market of healthcare platforms could reduce patients' searching cost; however, based on our analysis, the transaction cost induced by information asymmetry, especially the unverifiable information provided by physicians, still cannot be reduced by the Internet or other HIT. Proposition 6 proposed one possible solution to alleviate the problem, i.e., increasing the platform's revenue from advertising. Because the high revenue from advertising would lower the platform's and physicians' incentives to bias diagnostic reports. Thus, the government or regulator could encourage healthcare platforms to get high revenue from advertising by reducing the tax rate on the income of advertising; or they can subsidize firms or organizations which want to advertise on healthcare platforms.

The second implication also comes from Proposition 6 which indicates that, reducing physicians' outside option could alleviate the bias. For instance, the government or regulator could increase the supply of physicians who are qualified to work online. This would increase the competition of the labor market of online physicians. It would further lower their outside option when they sign contract with the platform. According to our prediction, low outside option would reduce the platform's cost of hiring physicians which would further decrease the registration fee. However, this gives the platform an incentive to reduce the discretion to increase the profit, which has been predicted in Proposition 4.

7 Conclusion

In this paper, we present a new model to study the healthcare platform's equilibrium discretion strategy (i.e., restriction to online physicians' diagnostic reports) and online physicians' reporting strategy when there is information asymmetry between patients and online physicians. The most interesting result we find is that truthfully reporting may not happen in equilibrium. This result does not arise from patients' preferences on diagnostic reports. Instead, it arises as an equilibrium result because rational healthcare platforms and physicians have desire to stay on the market for the long-term returns of reputation. When the platform tolerates biases, it has to lower its registration fee to maintain profit. However, if they do not value the market reputation, the platform would not grant any freedom to physicians' diagnostic reports, i.e., no biased report would be generated in equilibrium.

Healthcare platforms are a product of innovation in the healthcare market. The outcome of innovation strongly depends on the government's preferences and actions. Therefore, in another extension, we could also consider more government behaviors in the model. Overall, our model can be the basic building blocks for future studies.

References

Agarwal, R., Gao, G., DesRoches, C., Jha, A.K.: The digital transformation of healthcare: current status and the road ahead. Inf. Syst. Res. **21**(4), 796–809 (2010)

Anderson, C.L., Agarwal, R.: The digitization of healthcare: boundary risks, emotion, and consumer willingness to disclose personal health information. Inf. Syst. Res. **22**(3), 469–490 (2011)

Armstrong, M., Zhou, J.: Paying for prominence. Econ. J. **121**(556), F368–F395 (2011)

Aron, R., Dutta, S., Janakiraman, R., Pathak, P.A.: The impact of automation of systems on medical errors: evidence from field research. Inf. Syst. Res. **22**(3), 429–446 (2011)

Arrow, K.J.: Uncertainty and the welfare economics of medical care. Am. Econ. Rev. **53**(5), 941–973 (1963)

Ayal, M., Seidman, A.: An empirical investigation of the value of integrating enterprise information systems: the case of medical imaging informatics. J. Manage. Inf. Syst. **26**(2), 43–68 (2009)

Bhargava, H.K., Mishra, A.N.: Electronic medical records and physician productivity: evidence from panel data analysis. Manage. Sci. **60**(10), 2543–2562 (2014)

Brandenburger, A., Polak, B.: When managers cover their posteriors: making the decisions the market wants to see. RAND J. Econ. **27**(3), 523–541 (1996)

Cornière, A., Taylor, G.: Integration and search engine bias. RAND J. Econ. **45**(3), 576–597 (2014)

Einav, L., Farronato, C., Levin, J.: Peer-to-peer markets. Ann. Rev. Econ. **8**, 615–635 (2016)

Einav, L., Levin, J.: Managed Competition in Health Insurance. Journal of the European Economic Association **13**(6), 998–1021 (2015)

Einav, L., Levin, J., Popov, I., Sundaresan, N.: Growth, adoption, and use of mobile e-commerce. Am. Econ. Rev. **104**(5), 489–494 (2014)

Eliaz, K., Spiegler, R.: A simple model of search engine pricing. Econ. J. **121**(556), F329–F339 (2011)

Goh, J.M., Gao, G., Agarwal, R.: Evolving work routines: adaptive routinization of information technology in healthcare. Inf. Syst. Res. **22**(3), 565–585 (2011)

Hagiu, A., Jullien, B.: Why do intermediaries divert search? RAND J. Econ. **42**(2), 337–362 (2011)

Hanauer, D.A., Zheng, K., Singer, D.C., Gebremariam, A., Davis, M.M.: Public awareness, perception, and use of online physician rating sites. JAMA **311**(7), 734–735 (2014)

Jack, E.P., Powers, T.L.: Volume flexible strategies in health services: a research framework. Prod. Oper. Manage. **13**(3), 230–244 (2004)

Jemal, A., Ward, E., Hao, Y., Thun, M.: Trends in the leading causes of death in the United States, 1970-2002. JAMA **294**(10), 1255–1259 (2005)

Johns Hopkins University: Chronic Conditions: Making the Case for Ongoing Care (2004). http://www.partnershipforsolutions.org/DMS/files/chronicbook2004.pdf. Accessed 10 July 2017

Khoumbati, K., Themistocleous, M., Irani, Z.: Evaluating the adoption of enterprise application integration in health-care organizations. J. Manage. Inf. Syst. **22**(4), 69–108 (2006)

Kohli, R., Tan, S.S.-L.: Electronic health records: how can is researchers contribute to transforming healthcare? MIS Q. **40**(3), 553–573 (2016)

Kraschnewski, J.L., Gabbay, R.A.: Role of health information technologies in the patient-centered medical home. J. Diab. Sci. Technol. **7**(5), 1376–1385 (2013)

Kydland, F.E., Prescott, E.C.: Rules rather than discretion: the inconsistency of optimal plans. J. Polit. Econ. **85**(3), 473–492 (1977)

Menon, N.M., Lee, B., Eldenburg, L.: Productivity of information systems in the healthcare industry. Inf. Syst. Res. **11**(1), 83–92 (2000)

Miller, A.R., Tucker, C.: Active Social media management: the case of health care. Inf. Syst. Res. **24**(1), 52–70 (2013)

Ozdemir, Z., Barron, J., Bandyopadhyay, S.: An analysis of the adoption of digital health records under switching costs. Inf. Syst. Res. **22**(3), 491–503 (2011)

Peng, G., Dey, D., Lahiri, A.: Healthcare it adoption: an analysis of knowledge transfer in socioeconomic networks. J. Manage. Inf. Syst. **31**(3), 7–34 (2014)

Prendergast, C.: A theory of "Yes Men". Am. Econ. Rev. **83**(4), 757–770 (1993)

Rajan, B., Seidmann, A., Dorsey, E.R.: The competitive business impact of using telemedicine for the treatment of patients with chronic conditions. J. Manage. Inf. Syst. **30**(2), 127–158 (2013)

The New York Times: Health Care, Uncertainty and Morality (2010). https://economix.blogs.nytimes.com/2010/08/13/health-care-uncertainty-and-morality/. Accessed 10 July 2017

Thorpe, K.E., Florence, C.S., Joski, P.: Which medical conditions account for the rise in health care spending? Health Aff. **36**(7), 437–445 (2004)

Tirole, J.: Hierarchies and Bureaucracies: on the role of collusion in organizations. J. Law Econ. Organ. **2**(2), 181–214 (1986)

Yan, L., Peng, J., Tan, Y.: Network dynamics: how can we find patients like us? Inf. Syst. Res. **26**(3), 496–512 (2015)

Yan, L., Tan, Y.: Feeling blue? Go online: an empirical study of social support among patients. Inf. Syst. Res. **25**(4), 690–709 (2014)

Zahedi, F.M., Walia, N., Jain, H.: Augmented virtual doctor office: theory-based design and assessment. J. Manage. Inf. Syst. **33**(3), 776–808 (2016)

The Power of Facebook and Instagram Fans: An Exploration of Fan Comments and Their Effect on Social Media Content Strategy

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Abstract. Organizations continue to invest in marketing strategies through various social media platforms in order to enhance engagement. Building engagement is said to help companies to gain more profit and contribute to their social responsibility (Du et al. 2010). Users follow companies for access to coupons, deals and events. Users like, retweet and share posts, and can recommend the company to family or friends via WOM. Understanding the drivers, process and importance of social media engagement behavior is highly relevant for social media managers. Their inferences are critical for the establishment of effective customer relationship, which directly affect the company's revenue. In this study, we examine the effect of user's comments, and the sentiment of these comments, on firms' social media content strategies. Previous research has demonstrated that engagement can be stimulated by firm strategies, however we consider a more dynamic relationship through the exploration of how firm strategy can be driven by social media engagement, and more specifically user comments. In doing so, this model contributes to a deeper understanding of the dyadic relationship between firm social media strategy and social media engagement.

Keywords: Social media · Content strategy · User engagement
User influence

1 Introduction

Social media (SM) can provide value to businesses by enabling the formation of online customer communities to support branding, sales, customer service, and product development (Culnan et al. 2010). Recent reports demonstrate that SM influences businesses' bottom line and brand image, and firms should strategise their social media

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presence to align it with their business strategies (Wessel 2011), because recent digital transformations have altered the role of customers from passive to active users. Active users can raise complaints or compliments publicly to a large audience in real time. Traditional customer relationship management (CRM) was designed to build and maintain profitable customer relationship by providing higher customer value and satisfaction (Sen and Sinha 2011), however social media platforms have changed the way firms build and maintain relationships with their customers. For example, SM enables customers to spread their thoughts and feelings to the vast amount of users, which can often be negative, and organizations have difficulties aligning their response strategies in such a dynamic, fast-moving environment (Schultz et al. 2012).

While, previous research has demonstrated that engagement can be stimulated by firm strategies (Dolan et al. 2016), in this study we consider a more dynamic relationship through the exploration of how firm strategy can be driven by social media engagement and more specifically user comments. As such, the proposed model contributes to a deeper understanding of the dyadic relationship between firm social media strategy and social media engagement.

This study aims to fill the gap in the literature about the dynamic nature of interaction with customers and firms by this **research question**: *"How is firms' social media strategy influenced by user engagement behavior?"*. Through investigating this question, we focus on the fundamental aspects of users' reverberate power provided by social media. The core idea is to examine the effect of social media engagement on firm content generation. We will analyze users fan page activities in one period and see the related effect on fan page content strategy including the frequency, format and tape of the posts on the following period.

2 Social Media Engagement

The conceptualization and definition of engagement varies across multiple disciplines and contexts. For example, organizational behavior literature suggests that engagement is physically, emotionally or cognitively expressed through task behaviors (Bowden 2009). By comparison, in the discipline of social psychology, engagement is described as an initiative and adequate response to social stimuli (Jennings and Stoker 2004). Within marketing and information system literature, engagement has been characterized as an ongoing emotional, cognitive and behavioral activation state (Brodie et al. 2011).

Scholars argue that customer engagement on social media platforms is the future of customer-firm interactions (Bijmolt et al. 2010). These newly minted active users raise complaints or compliments about firms on social media platforms and it has been shown that firm behavior or actions affect customer engagement on firm social media pages, and the engagement effect is stronger for loyal customers (Rishika et al. 2013). We posit the flip side and ask if increase in engagement leads to changes in firms' strategy. Answering this question helps social media researchers and marketers to find the missing link of the user and firm interaction dynamics. We want to investigate about the effect and power of users in leading social media content generation process.

Since social media entices both positive and negative sentiments/comments from the users, it is a double-edged sword for businesses (Gu and Ye 2014). Therefore, understanding user behavior and strategies employed in user-firm interactions would help firms in developing effective social media strategies. Researchers have categorized users based on their observed behavior and interaction with other users. It has been shown that users with high levels of engagement in company fan page have high level of engagement with the firm's product and brands (McAlexander et al. 2002).

User comments on the firms' social media content have the potential to be positive or negative for the firm, based on the valence of the content (Van Doorn et al. 2010). Positively-valenced engagement behavior is reflected in favourable or affirmative behaviors, whereas negatively-valenced engagement behavior is exhibited through unfavorable behaviors (Hollebeek and Chen 2014). Positively-valenced behaviors often reflect heightened levels of customer engagement and include activities such as 'sharing' a brand post to a friend with a recommendation to experience the offer (Van Doorn et al. 2010). We propose that this will have different effects on firm social media strategy. Remember that the model is all about comments and sentiment and the effect of this.

While the nature of social media influences the degree to which customers engage with the organization (Malthouse et al. 2013), little research has investigated how engagement, in particular the sentiment of this engagement may affect the organizational level decisions.

3 Social Media Content Strategy

Researchers agree that relevant, appropriate and valuable content is critical for social media engagement on fan pages. However, one needs to understand how customers value content and why do they even engage with fan pages. Extant literature suggests four main reasons for customer engagement- social interactions (Ashley and Tuten 2015; Park et al. 2009), informational needs (Cvijikj and Michahelles 2013), entertainment needs (De Vries et al. 2012) and monetary incentives. Social interaction in fan pages refers to writing comments, feedback, propagating information by sharing, liking and etc.

Customers engage with fan page if content provided there fulfills their information needs. Therefore, the message might address functional appeals, experiential appeal or comparative appeal (Ashley and Tuten 2015). The information might be about product deals, availability, price and product related aspects. Therefore, content categories including educational, functional and employee brand posts fit to the informational message strategy. Interactional content emphasis on the consumer-brand interactions that materialize in social media channels. For instance, contents related to current events, personal, brand community and customer relationship is considered interactional content. Other content categories such as emotional, experiential, brand resonance and social causes address transformational content strategy (Tafesse and Wien 2017). We group all these 12 content categories in three broader message strategy (i.e., transformational, informational and interactional), we plan to study the effect consumer engagement behavior on each type of the related content that will be generated on the next period.

This study offers a detailed exploration of which type of content is more favorable from the user point of view and does this attraction has any effect on the firm content strategy. The conceptual model extends the work of recent scholars (De Vries et al. 2012; Dolan et al. 2016; Lee et al. 2013) to include twelve brand post strategies Tafesse and Wien (2017). In the current models in the literature, social media content is studied in more general categories. But in this research for increasing the research accuracy, precision and reliability, we analyses social media content in more detail level and then combine the result of first stage in three broader categories.

Content Freshness

Freshness (recency) (Lewandowski 2008) is the amount of firm activity on its own fan page and captures the recency of a new content. Chung et al. (2014) address this strategy as the influence duration in their studies. Freshness is calculated by the average time gap between two successive posts by a firm in a given period (e.g., every fortnight). A few recent studies like Chung et al. (2014) have argued that the amount of firm social media activities has direct effect on social media engagement. In this situation they could earn considerable respect and could imagine corresponding returns in the future (Kankanhalli et al. 2005; Wasko and Faraj 2005).

In this research we focus on the content freshness. In this research we will concentrate on firm proactive content generation role of firms on their fan pages. In future studies we can include firms' passive role in terms of responding to users in the conceptual model.

4 Theory, Methodology, and Research Design

Customers and firms flock to social media platforms, often with different objectives. For example, while customers may engage with firms on social media platforms to complain or complement about products/services, aftersales and information about promotions and vouchers, firms may solicit customers to increase brand awareness, advertising and learn about their market and competition. Therefore, we argue that customers and firms may find themselves misaligned in terms of content strategy on fan pages. Indeed, recent studies have shown how firms and customers tend to focus on different topics on social media platforms (Shahbaznezhad 2016a; b).

User on social media platforms are heterogeneous not only in their preferences for content but also in their engagement (Shahbaznezhad and Tripathi 2015), hence, it is often challenging for firms to understand the myriad of user engagement strategies from different user types and translate that into their social media content strategies. Therefore, we posit, that investigating the effect of user engagement on firms' social media content strategies is anything but trivial.

We draw from Actor-network theory (ANT) in order to explore our conceptual model. ANT introduces actor-network as the heterogeneous network of aligned interests, including people, organizations and standards that interacting in the context of technological artefacts (Walsham 1997). ANT concentrates on the infrastructure of actor-networks and try to answer how they are formed, how they can fall apart not attempt to explain why a network exists. Through relying on this theory we can justify why social media engagement behavior that are represented by users (human) is an important to be addressed as the driver of this study and conceptual model. Actors operate in the context of rules and strategies that are designed by fan page owners (companies). Actors' perceptions and interactions are guided by rules. Within social media platforms, Actors such as fans share perceptions, problem-agendas, norms, preferences, etc. They tell similar stories of their past and future in a network.

In addition, social rule system theory guides the development on the conceptual model. Burns and Flam (1987) attempt to analyze the dynamic relationships between actors and structure. In this theory human agency, strategic behavior and struggles are important but situated in the context of wider structures. Actors interact within the constraints and opportunities of existing structures and they restructure these systems simultaneously. The added value of this dynamic interaction is that the 'rules of the game' are not fixed, but may change during the game, over time. The notion of 'playing games' also highlights that social (inter)action is not necessarily harmonious. The consequence of these multiple games is that elements of these systems co-evolve (Geels 2004).

We take the concept of users as game changers (Osterwalder and Pigneur 2010) to employ the aforementioned theories to scrutinize the dynamic relationship between users and firms in social media fan pages. We investigate the signals from users and explore the way in which firms may change their approach on their fan pages as a result. As such, we have collected data from four pacific airlines and three platforms including Facebook, twitter and Instagram over a 12 month period. The dataset was split into two sections and we will study the effect of social media engagement in the first period on the firms' content strategy on the second time period. Figure 1 provides the conceptual model of the proposed relationships between social media engagement behavior and firms content strategy.

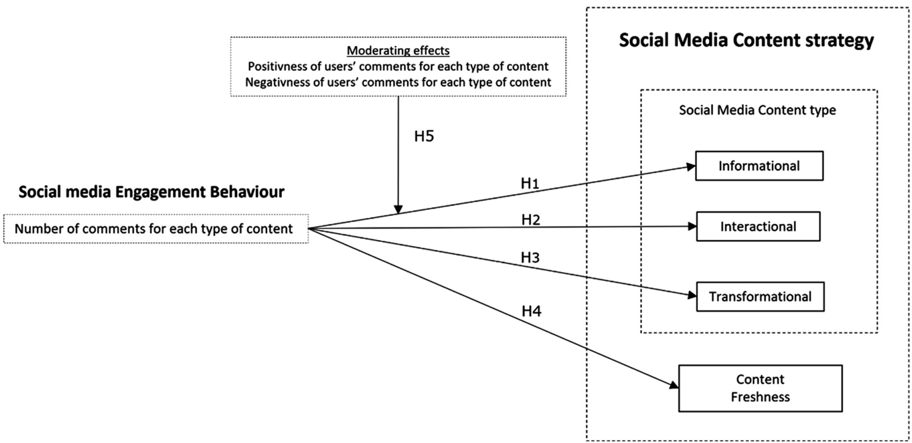

Fig. 1. Proposed conceptual model

Social media engagement behavior includes the number of comments, positiveness and negativeness of comments, number of likes, and number of shares for each post. In this research we concentrate on the active engagement behavior that is commenting. As it discussed former, comment sentiment can be important that we take into consideration in our research design. Social media content strategy includes two overarching elements; content type and freshness. Content type is categorized into three main categories as informational, interactional, and transformational. These categories covers 12 specific brand post elements as conceptualized by Tafesse and Wien (2017). The research will influence of communication on social media engagement behavior and demonstrates how social media engagement behavior (shown in H1–H5) may influence social media content strategy. Figure 1 demonstrates the hypothesized relationships between these constructs.

The Main Hypotheses Are:

Firstly, it is hypothesized that when specific types of content (i.e. informational, interactional, and transformational) receive an increased number of comments, firms will be likely to alter their social media content strategy in the form of increasing the use of the type of informational, interactional, or transformational content. As such, we predict:

H1. The number of comments made on informational content is significantly and positively related to an increase in informational content use.
H2. The number of comments made on interactional content is significantly and positively related to an increase in interactional content use.
H3. The number of comments made on transformational content is significantly and positively related to an increase in transformational content use.

Additionally, a significant relationship is expected to occur between the number of comments and the frequency at which new content is posted by the firm. An increase in the number of comments is hypothesized to increase content freshness (i.e. more frequent posting). Comparatively, a decrease in the number of comments may cause a firm to post content less frequently, hence reducing content freshness. As such, we predict:

H4. The number of comments made on each type of content is significantly and positively related to content freshness
H4a. An increase in the number of comments for each type of content will increase content freshness
H4b. A decrease in the number of comments for each type of content will reduce content freshness

Finally, our research considers the moderating role of content sentiment on the relationship between the number of comments and the firm's social media content strategy. Firms that receive negative comments on specific types of content may decrease their use of that content, whereas positive comments are likely to result in an increase of related content, hence significantly impacting on social media content strategy. Therefore, we predict:

H5. The relationship between the number of comments and each social media content type is positively (negatively) moderated by the positiveness (negativeness) of comments.

Empirical research is being conducted to apply the model to a dataset collected from four major Pacific airlines; Air New Zealand, Jetstar, Qantas and Virgin Australia. We selected airline industry with limited service to control for homogeneity of product type and controlling the indirect effect of social media behavior. This study uses a novel approach to data collection, through Facebook, and Instagram API to extract data from airline industry. This process generated 8 sub-sets of data (4 airlines on 2 platforms), allowing analysis of social media engagement behavior and brand post strategy across and between brands and platforms. In this study, we employ multivariate analysis of variance to perform data analysis and find the significance relationship between different variables in our theoretical model.

In this study we measure user engagement by the number of users comments for content categories (informational, interactional, and transformational), however, rich social media technologies allow for a wide range of measures to capture user engagement, such as measuring the temporal nature of user engagement, depth and breadth of user engagement, diversity of user base, etc. Further, the dynamic and temporal nature of these engagements may require longitudinal models to examine the effect of user engagement on firms' social media content strategies.

5 Results and Expected Outcomes

Theoretical and practical outputs from this research are expected. The key theoretical result of the complete paper is to contribute to the social media literature by proposing a model covering the overlooked areas in the firm decision making process in social media environment. Uncovering existing behavioral and technological patterns in the commercial-based communication is an expected result. This result provides an ontology of the underlying components of customers and firm relationship from a socio-technical point of view. Therefore, by discovering types of user's engagement in firm's social media fan page we will create the chance of contributing to motivational and behavioral aspects of online customers from a sociology and marketing perspective. Recognizing the factors affecting and predicting firms' behavior to continue or change their engagement strategy over time is the anticipated result. As a product of answering these two questions, online behavioral learning would be our contribution to the literature.

Furthermore, the projected research has potential for practical entailments for social commerce environment partners. At the end, firms can find better intuition about the different types of problems, market strategies, ways of applying different mechanisms and platforms, and different types of customer intentions.

6 Conclusion

Social media users can produce immediately huge waves of outrage that is called online firestorms (Huber et al. 2012). These firestorms impose new challenges to the firms. In this way, roles of the firms in social media bring new concerns for companies' strategists. As Culnan et al. (2010) discussed, in the absence of the capability to outline and measure the results of social media strategies, it is challenging that firms align their fan page initiatives with organizational goals and generate business value. This research will investigate the effect of the current users comments (both positive and negative in sentiment) on the firms future actions, specifically, their social media content strategy. Therefore, we conceptualized the potential effects of social media engagement- comments on fan page content strategy over time. The main assumption of this research is that firms as active actors consistently monitor their social media fan pages and following their observation they readjust firms' strategies.

References

Ashley, C., Tuten, T.: Creative strategies in social media marketing: an exploratory study of branded social content and consumer engagement. Psychol. Mark. **32**(1), 15–27 (2015)

Bijmolt, T.H., et al.: Analytics for customer engagement. J. Serv. Res. **13**(3), 341–356 (2010)

Bowden, J.L.-H.: The process of customer engagement: a conceptual framework. J. Mark. Theory Pract. **17**(1), 63–74 (2009)

Brodie, R.J., Hollebeek, L.D., Jurić, B., Ilić, A.: Customer engagement: conceptual domain, fundamental propositions, and implications for research. J. Serv. Res. **14**(3), 252–271 (2011)

Burns, T.R., Flam, H.: The Shaping of Social Organization: Social Rule System Theory with Applications. Sage Publications, London (1987)

Chung, S., Animesh, A., Han, K., Pinsonneault, A.: Firm's social media efforts, consumer behavior, and firm performance (2014)

Culnan, M.J., McHugh, P.J., Zubillaga, J.I.: How large us companies can use twitter and other social media to gain business value. MIS Q. Exec. **9**(4), 243–259 (2010)

Cvijikj, I.P., Michahelles, F.: Online engagement factors on Facebook brand pages. Soc. Netw. Anal. Min. **3**(4), 843–861 (2013)

De Vries, L., Gensler, S., Leeflang, P.S.: Popularity of brand posts on brand fan pages: an investigation of the effects of social media marketing. J. Interact. Mark. **26**(2), 83–91 (2012)

Dolan, R., Conduit, J., Fahy, J., Goodman, S.: Social media engagement behaviour: a uses and gratifications perspective. J. Strateg. Mark. **24**(3–4), 261–277 (2016)

Du, S., Bhattacharya, C.B., Sen, S.: Maximizing business returns to corporate social responsibility (Csr): the role of Csr communication. Int. J. Manage. Rev. **12**(1), 8–19 (2010)

Geels, F.W.: From sectoral systems of innovation to socio-technical systems: insights about dynamics and change from sociology and institutional theory. Res. Policy **33**(6), 897–920 (2004)

Gu, B., Ye, Q.: First step in social media: measuring the influence of online management responses on customer satisfaction. Prod. Oper. Manag. **23**(4), 570–582 (2014)

Hollebeek, L., Chen, T.: Exploring positively-versus negatively-valenced brand engagement: a conceptual model. J. Product Brand Manag. **23**(1), 62–74 (2014)

Huber, J., Landherr, A., Probst, F., Reisser, C.: Stimulating user activity on company fan pages in online social networks. In: ECIS, p. 188 (2012)

Jennings, M.K., Stoker, L.: Social trust and civic engagement across time and generations. Acta Polit. **39**(4), 342–379 (2004)

Kankanhalli, A., Tan, B.C., Wei, K.-K.: Contributing knowledge to electronic knowledge repositories: an empirical investigation. MIS Q. **29**(1), 113–143 (2005)

Lee, D., Hosanagar, K., Nair, H.: The effect of advertising content on consumer engagement: evidence from Facebook. Available at SSRN 2290802 (2013)

Lewandowski, D.: A three-year study on the freshness of web search engine databases. J. Inf. Sci. **34**(6), 817–831 (2008)

Malthouse, E.C., Haenlein, M., Skiera, B., Wege, E., Zhang, M.: Managing customer relationships in the social media era: introducing the social CRM house. J. Interact. Mark. **27**(4), 270–280 (2013)

McAlexander, J.H., Schouten, J.W., Koenig, H.F.: Building brand community. J. Mark. **66**(1), 38–54 (2002)

Osterwalder, A., Pigneur, Y.: Business Model Generation: A Handbook for Visionaries, Game Changers, and Challengers. Wiley, Hoboken (2010)

Park, N., Kee, K.F., Valenzuela, S.: Being immersed in social networking environment: Facebook groups, uses and gratifications, and social outcomes. CyberPsychol. Behav. **12**(6), 729–733 (2009)

Rishika, R., Kumar, A., Janakiraman, R., Bezawada, R.: The effect of customers' social media participation on customer visit frequency and profitability: an empirical investigation. Inf. Syst. Res. **24**(1), 108–127 (2013)

Schultz, D., Malthouse, E., Pick, D.: From CM to CRM to CN^2: a research agenda for the marketing communications transition. In: Eisend, M., Langner, T., Okazaki, S. (eds.) Advances in Advertising Research (Vol. III). EAA, pp. 421–432. Springer, Wiesbaden (2012). https://doi.org/10.1007/978-3-8349-4291-3_32

Sen, A., Sinha, A.P.: It alignment strategies for customer relationship management. Decis. Support Syst. **51**(3), 609–619 (2011)

Shahbaznezhad, H.: Fan page management via content generation and feedback strategies. In: PACIS 2016 Proceedings (2016a)

Shahbaznezhad, H., Tripathi, A.K.: Customer and firm interactions on social media. In: 19th Pacific Asia Conference on Information Systems, Singapore (2015)

Shahbaznezhad, H., Arvind, K.: The art of listening on social media platforms: how firms follow users on social media fan pages. In: Twenty-Fourth European Conference on Information Systems (ECIS), Istanbul, Turkey (2016b)

Tafesse, W., Wien, A.: A framework for categorizing social media posts. Cogent Bus. Manag. **4**(1), 1284390 (2017)

Van Doorn, J., et al.: Customer engagement behavior: theoretical foundations and research directions. J. Serv. Res. **13**(3), 253–266 (2010)

Walsham, G.: Actor-network theory and IS research: current status and future prospects. In: Lee, A.S., Liebenau, J., DeGross, J.I. (eds.) Information Systems and Qualitative Research. ITIFIP, pp. 466–480. Springer, Boston (1997). https://doi.org/10.1007/978-0-387-35309-8_23

Wasko, M.M., Faraj, S.: Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. MIS Q. **29**(1), 35–57 (2005)

Wessel, R.: Activist investors turn to social media to enlist support. New York Times (24) (2011)

Trial and Pricing Strategies of Software Market with Competition and Network Effects

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Abstract. In this paper, we develop a framework to generally characterize the equilibrium trial and pricing strategies of oligopoly software market, when there exist competition, network effects (externalities), uncertainty on software functionality, network maintaining cost and compatibility issues. We find that, in equilibrium, the restriction on network effects is decreasing with network effects, but increasing with consumers' basic willingness to pay. Meanwhile, the restriction on functionality is increasing with the posterior on the functionality after trial. The equilibrium price has a non-linear relation with the equilibrium network effects in a monopoly market and a market with completely incompatible software. However, the equilibrium price is set to maintaining cost in a market with completely compatible software. Moreover, we find that incompatibility could generate an equilibrium under which identical firms choose different trial and pricing strategies, and all consumers who want to purchase software are divided by firms on the market.

Keywords: Software trial · Pricing · Market competition
Network effects · Compatibility

1 Introduction

Different free trial strategies (policies) have been adopted by software firms to promote their products in the last two decades, and they have become increasingly popular. Current research on software trial, in terms of both empirical studies (e.g., Lee and Tan (2013)) and theoretical studies (e.g., Cheng and Tang (2010), Cheng and Liu (2012), Niculescu and Wu (2014)) pointed out that, there are two general forms of software trial on market: time-locked free trial and free "demo". However, one critical limitation of these studies is that they only focused on a monopoly market. We thus develop an oligopoly model to analyze optimal trial and pricing strategies, when there are both competition and network effects on software market. Our model differs from previous research in three ways: (1) we have two competing firms that produce software with the same functionality

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but may have different network effects; (2) we address the issue of "compatibility" or"standardization" on information goods; (3) we characterize a more general trial strategy.

Our model differs from previous research in three ways:

1. We have two software firms competing on the market. They produce software with the same functionality but may have different network effects.
2. We consider the issue of "compatibility" or"standardization" on information goods.
3. We seek to find the trial strategies in a more general way, rather than only focus on one specified trial strategy, e.g., time-locked free trial or free "demo" version with limited functionality.

Our paper mainly contributes to the research on product (software) trial and sampling in the information systems and marketing literature. Previous theoretical research on sampling, such as Goering (1985), Heiman et al. (2001), focused on consumer learning on physical products during trial process. Their results provided insights on the optimal sampling effect of a firm over time and the dynamic of product diffusion. Bawa and Shoemaker (2004) studied the effect of free sampling of physical goods, and found that free samples can really influence the firms' sales in the long term. Amir Heiman (1996) studied the optimal demonstration time of physical goods, such as motor vehicle and computer hardware. This is related to time-locked trials which are popular in the software industry.

Recent theoretical research by Dey et al. (2013) addressed the software free trial issue specifically. They focused on the time-locked trail of software, and studied the optimal time-locked trial from the view of consumer learning. In our view, the studies by Cheng and Tang (2010), Cheng and Liu (2012), are perhaps the most relevant ones to our research. Their results indicated that the monopolist's optimal trial strategies are closely related to the network effects. Empirical research on software trial is still limited. Lee and Tan (2013) used data from Download.com to study what factors make free-trial software more attractive than others. They found that user ratings influence the performance of software free trial through a diffusion process.

One critical limitation of these studies is that they assume the market is occupied by a monopolist. This could simplify the analysis. However, we cannot figure out how the market power would influence the market equilibrium and social welfare. Meanwhile, previous research, e.g., Brynjolfsson and Kemerer (1996), Economides and Katsamakas (2006), Sen (2007), has noticed that software market competition could largely influence equilibrium price, sales, profitability, and social welfare. Our paper thus differs from previous research on software trial by introducing market competition. We find that, the competition would induce multiple equilibria, extending the set of optimal trial and pricing strategies. Therefore, our results have more implications.

2 Model

2.1 Firms

Let us consider an environment with two software firms (oligopoly), and each of them only produces one software. The software is perfectly substitute to each other on the functionality, i.e., they have the same functionality, but may not be compatible to each other. The compatibility issue will be explained later. We assume that the full functionality is only privately observed by each firm, but not by consumers. Therefore, each firm has incentive to signal their common functionality to consumers through a proper designed trial strategy. Formally, we assume the full functionality $\tilde{s} \in \{s, 0\}$ is a random variable.

Each firm $i \in \{1, 2\}$ *simultaneously* (i.e., independently) develops its own software, and releases it to a market with its own trial strategy[1] $(A_i, B_i) \in [0, 1] \times [0, 1]$ and price $p_i > 0$. Here, the free trials would put *restrictions* on both software functionality and network effects. After consumers' free trial and purchase, all firms simultaneously choose their network size of their software $\mathbf{y} = (y_1, y_2)$ to match the consumers' expectation on the size of network.

To simplify analysis, we normalize the fixed cost, such as the development cost, to zero. But the firm has to pay a network maintaining cost $cy_i > 0$. Here, the marginal maintaining cost, c, is assumed to be the same across firms on the market. Therefore, each firm i chooses price and network size to maximize profit:

$$\max_{p_i, y_i} \pi_i \equiv (p_i - c)y_i$$

given the constraints from the consumer side which will be specified subsequently.

2.2 Consumers

We have a continuum number of consumers who treat software as a durable good. Without loss of generality, we normalize the total consumer on the market to a unit interval $[0, 1]$. They are assumed to be heterogeneous on their value of software network effects after trial, but are homogeneous on their evaluations of software network effects and functionality.

The consumers are divided into two types, $\theta_2 > \theta_1 > 0$, according to their value on the network effects. They are assumed to be distributed according to (probability) $(\theta_1, \theta_2) \sim (r_1, r_2)$, where $r_1 > r_2 > 0$, $r_1 + r_2 = 1$. To simplify analysis, but without loss of generality, we further assume that $r_1 - \frac{1}{2} = \frac{1}{2} - r_2 = \Delta > 0$. Specifically, consumers of type $\theta_j \in \{\theta_1, \theta_2\}$ have a utility defined as

$$u_j(d) = d\Big(\theta_j A_i + ky_i^e + \beta B_i s - p_i\Big) + (1 - d)\sum_i (A_i^2 ky_i^e + B_i^2 s)$$

[1] More precisely, from the language of game theory, the strategies $A_i(\cdot)$ and $B_i(\cdot)$ should be functions of history, which is null here. To simplify notation, we simply use A_i and B_i.

Here, $p_i > 0$ is the price charged by firm i. Consumers choose $d \in \{0,1\}$ to maximize their utilities, and $d = 1$ means purchasing a copy of software from firm i, and $d = 0$ means no purchase. In this preference, we first assume that consumers value network effects of software. Second, because the software is perfectly substitute on functionality, we assume that each consumer would only try and purchase from one firm.

We assume that the *willingness to pay* for the software after free trial is

$$\theta_j A_i + k y_i^e + \beta B_i s$$

where θ_j characterizes the type of consumers' marginal value on network effects. In order to connect results in this paper to future empirical test, we explain this type θ_j as the correlation between full network effects and consumers' profession. The full functionality s can be experienced if the consumer purchases it. Each firm's trial strategy profile is defined as a tuple $(A_i, B_i) \in [0,1] \times [0,1]$, where A_i is the part applying to the network effects, and B_i is the part applying to the full functionality. In this setup, we also assume that there is no income effect.

2.3 Timing

1. Software firms release their software with trial strategies (A_i, B_i) and price p_i, for $i = 1,2$. Consumers form a common prior on the functionality of the software on the market.
2. Each consumer chooses only one software from the market and forms expectation on the size of network, $\mathbf{y}^e = (y_1^e, y_2^e)$. They try it without paying anything and decide whether to pay for it according to the price p_i after the trial. The posterior on functionality is formed after trial, and it is publicly realized.
3. After consumers' purchase, the network size(s) (outputs), $\mathbf{y} = (y_1, y_2)$, is realized according to consumers' purchase volume.

We do not explicitly model the expectation forming process here. However, following Katz and Shapiro (1985) we would require that in equilibrium the consumers' expectations are fulfilled. Meanwhile, we also assume that:

Assumption 1. For any type of consumers, they have identical expectation on the network size.

In order to make the decision problem well defined and avoid tedious technical problems, such as negative price or probability in equilibria, we further assume that:

Assumption 2.

$$\theta_2 < k r_2$$

2.4 Equilibrium

The solution concept we are using here is Subgame Perfect Equilibrium with *Fulfilled Expectations* on network size[2] (SPEwFE). Formally, SPEwFE is a strategy profile

$$\Big((A_i^*, B_i^*, p_i^*, y_i^*), (d_j^*, y_j^e)\Big)$$

such that for every firm $i \in \{1, 2\}$ and every consumer of type $\theta_j \in \{1, 2\}$:

1. d_j^* maximizes type θ_j consumers' utility, for any firms' strategies (history), (A_i, B_i, p_i, y_i), and $y_j^e = y_i^*$;
2. $(A_i^*, B_i^*, p_i^*, y_i^*)$ maximizes firm i's profit, given consumers' d_j^* and $y_j^e = y_i^*$.

3 Analysis

In this section, we would characterize the equilibria. Following backward induction, we first go through consumer's optimal purchase decision. This would further help us determine the network size of each software. For any consumers of type θ_j, where $j \in \{1, 2\}$, they would purchase the software $i \in \{1, 2\}$, if and only if the purchase gives them at least as much as they can get from keeping the free trial, i.e., $u_j(d = 1) \geq u_j(d = 0)$. This induces that, in order to get type θ_j consumers to purchase this software, the market price charged by firm i should satisfy

$$0 < p_i \leq \theta_j A_i + ky_i^e + \beta Bs - \frac{1}{2}A_i^2 ky^e - \frac{1}{2}B_i^2 s$$

We now define $p_i(\theta_j, y_i^e) \equiv \theta_j A_i + ky_i^e + \beta B_i s - \frac{1}{2}A_i^2 ky_i^e - \frac{1}{2}B_i^2 s$.

3.1 Benchmark (Monopolist)

We first consider a market with a monopolist and characterize the optimal trial strategy and price. The time line is the same as the one specified before, but we only replace the two firms with one firm. Following backward induction, given the consumers' optimal decisions, the monopolist's optimal decision problem is to solveo

$$\max_{A,B,y^e} \Big(\theta_j A + ky^e + \beta Bs - \frac{1}{2}A^2 ky^e - \frac{1}{2}B^2 s - c\Big)y^e$$

Because we only have one firm on the market, the subscript has been removed. In the above optimal decision problem, the firm only needs to choose trial strategy (A, B) and the network size y^e. The next result characterizes the monopolist's optimal decision.

[2] See Katz and Shapiro (1985) for the definition of *Fulfilled Expectation Cournot Equilibrium*. Ours is based on their equilibrium solution concept.

Proposition 1. *In the monopoly case, if it is true that*

$$\theta_2^2 > \theta_1^2 + 2k^2 r_1 r_2 + 2k^2 r_1 + 2kr_1(\frac{1}{2}\beta^2 s - c)$$

the monopolist would set

$$(A^m, B^m) = (\frac{\theta_2}{kr_2}, \beta) \qquad \textit{and} \qquad p^m = p^*(\theta_2, r_2) = \frac{1}{2}\frac{\theta_2^2}{kr_2} + kr_2 + \frac{1}{2}\beta^2 s$$

and the equilibrium network size is $y^* = r_2$. Otherwise, it would set

$$(A^m, B^m) = (\frac{\theta_1}{k}, \beta) \qquad \textit{and} \qquad p^m = p^*(\theta_1, 1) = \frac{1}{2}\frac{\theta_1^2}{k} + k + \frac{1}{2}\beta^2 s$$

then all consumers purchase the software, and network size is $y^* = 1$.

Due to page limit, we would only explain intuition of the results. All proofs are available upon request. This result implies that: when the difference of BWTP between the two types of consumers is not large enough, which is measured by $\theta_2^2 - \theta_1^2$, the monopolist would prefer a large network size to a small one, i.e., targets all the consumers on the market. Meanwhile, a stingy trial strategy is released in the trial period to lower the cost generated by demand cannibalization. The key point here is that, θ_1 consumers occupy a large share in the population. Then, a large demand cannibalization would also be generated by these consumers. Therefore, firm would choose to limit the functionality or network effects to encourage θ_1 consumers to purchase after trial. In the meantime, a higher price still can be generated through the large network size.

Now, we would consider two different markets: (1) a market with completely compatible software, and (2) a market with completely incompatible software, respectively. Following the literature, e.g., Katz and Shapiro (1985), Economides (1996), the key difference between these two markets is on the formation of networks:

1. In a *market with completely compatible software*, the network would be shared among all software firms, i.e., $y_i^e = y_1 + y_2$.
2. In a *market with completely incompatible software*, the network would not be shared among all software firms, and each software exclusively has its own network, i.e., $y_i^e = y_i$.

3.2 Market with Completely Compatible Software

If a software market has more than one firm, then each firm's decision would also be based on the competitor's strategies. Firms would trade off between matching the competitor's trial strategy, network effects and price or trying something different. The following results show that, if the software on the market is compatible with each other, then in (pure strategy) equilibrium, each firm would choose the same market price. However, they might use different trial strategies.

Proposition 2. *In equilibrium:*

1. *For each firm, the optimal trial strategies would be determined by*

$$\theta_j A_i^* + k + \beta B_i s - \frac{1}{2}A_i^{*2}k - \frac{1}{2}B_i^{*2}s = c$$

   and price equal the marginal maintaining cost, i.e., $p_i^* = c$, *where* $i \in \{1, 2\}$.
2. *Given firms' strategies, all consumers try both software with equal chance and purchase after trial.*
3. *Two firms divide the two types of consumers equally, i.e.,* $y_1^* = y_2^* = \dfrac{1}{2}$. *Then the network size is* $y^* \equiv y_1^e = y_2^e = 1$.

In this equilibrium, two firms divide the market equally and charge the same price which is just enough to cover the marginal maintaining cost c. The intuition is as follows: software on the market is completely compatible with each other; therefore, consumers would perfectly share the network effects. This induces that two software on the market are completely substitute to each other on both functionality and network effects. Then the argument here would be similar to the classical Bertrand model, and the equilibrium price of each firm would be equal to the marginal maintaining cost.

3.3 Market with Completely Incompatible Software

In this section, we consider the case in which the software from two firms are completely incompatible with each other. If it is completely incompatible, the network size would be different if firms target different types of consumers. Firms and consumers will not share the aggregate network size any more. This generates a new trade-off: given the competition on the market, on the one hand, a firm could try to exclusively attract a large share of consumers on the market, so as to charge a high price through high willingness to pay. However, it has to pay a high maintaining cost. On the other hand, firms could share the market with the competitor and get a small network size, but only a low maintaining cost would be paid.

In the next result, we find that, given the same parameter space, there exist multiple equilbria if the software is completely incompatible. This result would never be true if the software is completely compatible with each other.

Proposition 3. *If it is true that*

$$1 < \frac{\theta_2}{\theta_1} < \frac{(1 + r_1)}{2r_1}$$

or

$$\theta_2^2 > \max\left\{\frac{(1 + r_1)^2}{4r_1^2}\theta_1^2, \quad \theta_1^2 + 2kr_1\Big(k(1 + r_2) + \frac{1}{2}\beta^2 s - c\Big)\right\}$$

there exists an equilibrium (non-symmetric) under which:

1. *Firm i sets $(A_i^*, B_i^*) = (\frac{\theta_1}{kr_1}, \beta)$, and $p_i^* = \frac{1}{2}\frac{\theta_1^2}{kr_1} + kr_1 + \frac{1}{2}\beta^2 s$. Firm j sets $(A_j^*, B_j^*) = (\frac{\theta_2}{kr_2}, \beta)$, and $p_j^* = \frac{1}{2}\frac{\theta_2^2}{kr_2} + kr_2 + \frac{1}{2}\beta^2 s$, where $i, j \in \{1, 2\}$ and $i \neq j$.*
2. *Consumers of type θ_1 try software i and purchase it after trial; consumers of type θ_2 try software j and purchase it after trial.*
3. *Firm i chooses $y_i^* = r_1$, and firm j chooses $y_j^* = r_2$.*

The above results demonstrate how the market competition would influence the equilibrium price and trial strategy:

1. If the difference between θ_2 and θ_1 is not large enough or the proportion of θ_1 consumers is large, then θ_1 consumers may not accept a larger network size, because the marginal payment for them to get the additional network effects is too high.
2. Meanwhile, when the difference between θ_2 and θ_1 is large enough or the proportion of θ_1 consumers is small, the firm would have no incentive to attract more consumers from the competitor, because additional benefit from high price is not enough to cover the maintaining cost generated from large network size. Therefore, firms would prefer to segment the market with different trial and pricing strategies.

We have another two equilibria under which two firms choose the same trial strategy and price in equilibrium. It is similar to the market with completely compatible software.

Proposition 4. *If*

$$\theta_2^2 > \theta_1^2 + 2k(r_1 - \frac{r_2}{2})(k\frac{r_1+1}{2} + \frac{1}{2}\beta^2 s - c)$$

there exists an equilibrium (symmetric) under which:

1. *Both firms set $(A_i^*, B_i^*) = (\frac{2\theta_2}{kr_2}, \beta)$, and $p_i^*(\theta_1, r_2/2) = \frac{\theta_2^2}{kr_2} + \frac{kr_2}{2} + \frac{1}{2}\beta^2 s$, where $i \in \{1, 2\}$.*
2. *Only consumers of type θ_2 try and purchase the two software with the same probability.*
3. *Both firms choose $y_1^* = y_2^* = \frac{r_2}{2}$, the market is equally divided by these two firms.*

The intuition of this result is as follows. When the share of the consumers with high BWTP is large, these consumers would have no incentive to try different software, given the same functionality. The reason is that the deviation would induce a lower price, but this benefit is not large enough to cover the lost from the decreased network effects. On the firm side, a deviation would generate a large network size, which would further induce a higher price. However, the cost of demand cannibalization would increase more than the profit from price increasing. Therefore, firm has no incentive to deviate.

Proposition 5. *Given that $\theta_2 > \theta_1 > 0$, there exists another equilibrium (symmetric) under which:*

1. *Both firms set $(A_i^*, B_i^*) = (\frac{2\theta_1}{k}, \beta)$, and $p_i^*(\theta_1, 1/2) = \frac{\theta_1^2}{k} + \frac{k}{2} + \frac{1}{2}\beta^2 s$, where $i \in \{1, 2\}$.*
2. *All consumers on the market try and purchase the two software with the same probability.*
3. *Both firms choose $y_1^* = y_2^* = \frac{1}{2}$, the market is equally divided by these two firms.*

In this result, both firms have incentive to attract as many consumers as possible. The reason is: larger network effects would be generated from a large base of consumers, then a higher price could be induced from the network effects through firm's trial strategy. This price premium would be larger than the cost of demand cannibalization. Therefore, both firms have incentive to attract all the consumers on the market.

4 Comparative Statics

The general optimal strategies of firms have been characterized in the above sections. We still seek to understand how market competition and consumers' preference, e.g., the posterior on functionality after free trial, would affect firms' optimal strategies and social welfare.

Proposition 6. *In the monopoly market and completely compatible market:*

1. *The equilibrium price is monotonic increasing with functionality.*
2. *There exists a $k^* > 0$, such that, for any $k \in (0, k^*]$, the market price is monotonic decreasing with the equilibrium network effects ky^*. For any $k \in (k^*, \bar{k}]$, the market price is monotonic increasing with the equilibrium network effects ky^*.*

The intuition of this result is as follows. First, consumers always prefer more functionality, therefore, firms would charge more for more functionality. The second observation is that market price has a non-linear relation with network effects. In particular, price would decrease first when the network effects are small, whereas it would increase after a cut-off value.

4.1 Monopoly vs Completely Compatible Market

Comparing Propositions 1 and 2, it is easy to check that, in the case of completely compatible market, the price paid by consumers is no more than the one in the monopoly case. We have the following result:

Proposition 7. *On the market with completely compatible software, the competition would induce the following results:*

1. *Each firm sets the same price which is no more than the monopoly price and gets zero profit.*
2. *Equilibrium network effects are no less than those of the monopoly market.*
3. *Consumer surplus is more than that of the monopoly market.*

4.2 Monopoly vs Completely Incompatible Market with Two Firms

If we have a market with completely incompatible software, the equilibrium results are quite different from those of the market with completely compatible software. The key difference is generated by the non-symmetric equilibria described in Proposition 3. Comparing Propositions 1 and 3, we find that there exist conditions under which the competition could induce a lower price to part of the consumers on the market, given that the software is completely incompatible with each other. This result is consistent with the classical theory on market competition, even if we have network effects here. We have the following result:

Proposition 8. *On the market with completely incompatible software, the competition would induce the following results:*

1. *For some parameter values, each firm would choose different optimal trial strategy and price, and all consumers can purchase software from one of the firms. The consumer surplus would be improved by competition. Meanwhile, the monopoly profit would be unequally divided between the two firms.*
2. *For some other parameter values, firms still equally divide the market, but the optimal trial strategies and price would be different from those of the monopoly market.*
3. *Firms get more profit than that of the completely compatible market.*

5 Put Optimal Trial Strategies to Work

In this section, we try to make the equilibrium strategies work and use our equilibrium results to explain the real trial strategies from different software firms.

5.1 Time-Locked Free Trial

Time-locked free trial is a very popular trial strategy which has been adopted by many software firms. We are going to demonstrate that the time-locked free trial is a special case of our results. In all the equilibria we have characterized in this paper, the optimal trial strategies (A_i, B_i) have the following form: $A_i^* = \frac{\theta'_j}{ky_i^*}$ and $B_i^* = \beta$. The price is $p_i^* = \frac{\theta_j\theta'_j}{2ky^*}+ky^* + \frac{1}{2}\beta^2 s$, where $\theta'_j, \theta_j \in \{\theta_1, \theta_2\}$, and y^* is the equilibrium network size.

5.1.1 Full Network Effects and Full Functionality in Trial

In any of the above equilibrium trial strategies, if we have $\frac{\theta'_j}{ky_i^*} = \beta$ and let $\mu_1 \equiv A_i^* = B_i^*$, then consumers' utility from trial can be transferred to $\frac{1}{2}\mu_1^2(ky^* + s)$, where y^* is the equilibrium network size. To implement this trial strategy, we can do the follows. First of all, during the trial period, the full network effects and functionality can be experienced by the consumers. Second, we only let consumers experience the full functionality and network during part of the life time, i.e., μ_1. Therefore, μ_1 here is exactly the time-locked free trial in reality. Based on the above results, we know that, time-locked free trial could be the optimal trial strategy in both the monopoly case and oligopoly case, no matter if the software on the market is compatible with each other.

5.1.2 Full Network Effects and Partial Functionality in Trial

If we have $\frac{\theta'_j}{ky_i^*} > \beta$ and let $\mu_2 \equiv B_i^*/A_i^* \in (0, 1)$. Then consumers' utility from trial is $\frac{1}{2}A_i^{*2}(ky^* + \mu_2^2 s)$. In this optimal trial strategy, consumers experience full network effects during trial time, but only part of the full functionality. To implement this trial strategy, we let the full network effects be experienced during the trial period, but the functionality be limited. Meanwhile, the same as the previous case, we only let consumers experience in part of the life cycle, i.e., A_i^*.

5.1.3 Partial Network Effects and Full Functionality in Trial

If we have $\frac{\theta'_j}{ky_i^*} < \beta$, and let $\mu_3 \equiv A_i^*/B_i^* \in (0, 1)$, then consumers' utility from trial can be transferred to $\frac{1}{2}B_i^{*2}(\mu_3^2 ky^* + s)$. In this optimal trial strategy, consumers experience part of the network effects during trial, but get full functionality of the software. To implement this trial strategy, we can give partial network effects to consumers during the trial period, but full functionality. Meanwhile, we only let consumers experience these in part of the software's life cycle, i.e., B_i^*.

6 Conclusion

We develop here a model to generally characterize the equilibrium trial and pricing strategies of software firms, when there exist competition, network effects, uncertainty on software functionality, network maintaining cost, and compatibility issues. Four questions in such setup are: (1) how would the network effects affect the equilibrium outcomes, e.g., trial and pricing strategies, sales, profits and consumer surplus; (2) whether the optimal trial strategy and price would change compared to the monopoly case; (3) whether consumer surplus would be improved after introducing competition; and (4) how would compatibility issues affect market equilibrium.

Our analysis first characterizes market equilibria under three different market structures: (1) a monopoly market, (2) a market with completely compatible software, and (3) a market with completely incompatible software. We find that: for any market structure, in optimal, the restriction on network effects is decreasing with network effects, but increasing with basic willing to pay. However, the restriction on functionality is increasing with the posterior on the functionality after trial. We also find that incompatibility could generate equilibria under which all consumers who want to purchase software are divided by firms on the market. However, this equilibrium does not exist in the other two market structures.

This paper focuses on static competition. However, in reality, software firms' trial and pricing strategies could be sequentially interacted. We could observe one incumbent releases a software with certain trial strategy and price; and subsequently, new entrant releases a software with similar functionality and chooses its own trial strategy and price. It is obvious that the incumbent's optimal decisions depend on the decisions of the follower. Additionally, consumers also face a dynamic decision problem. The basic trade-off for the consumers is to try and purchase before the new product or try until the new software is released. Facing this constraint, the firms' optimal trial and pricing strategies would also change accordingly. The results might be different from our results here. Meanwhile, the dynamic analysis could also help us refine the multiple equilibria we have characterized in this static setup. This might bring us more insights and testable results.

References

Amir Heiman, E.M.: Using demonstration to increase new product acceptance: controlling demonstration time. J. Market. Res. **33**(4), 422–430 (1996)

Bawa, K., Shoemaker, R.: The effects of free sample promotions on incremental brand sales. Market. Sci. **23**(3), 345–363 (2004)

Brynjolfsson, E., Kemerer, C.F.: Network externalities in microcomputer software: an econometric analysis of the spreadsheet market. Manage. Sci. **42**(12), 1627–1647 (1996)

Cheng, H.K., Liu, Y.: Optimal software free trial strategy: the impact of network externalities and consumer uncertainty. Inf. Syst. Res. **23**(2), 488–504 (2012)

Cheng, H.K., Tang, Q.C.: Free trial or no free trial: optimal software product design with network effects. Eur. J. Oper. Res. **205**(2), 437–447 (2010)

Dey, D., Lahiri, A., Liu, D.: Consumer learning and time-locked trials of software products. J. Manag. Inf. Syst. **30**(2), 239–268 (2013)

Economides, N.: The economics of networks. Int. J. Ind. Organ. **14**(6), 673–699 (1996)

Economides, N., Katsamakas, E.: Two-sided competition of proprietary vs. open source technology platforms and the implications for the software industry. Manage. Sci. **52**(7), 1057–1071 (2006)

Goering, P.A.: Effects of product trial on consumer expectations, demand, and prices. J. Consum. Res. **12**(1), 74–82 (1985)

Heiman, A., McWilliams, B., Shen, Z., Zilberman, D.: Learning and forgetting: modeling optimal product sampling over time. Manage. Sci. **47**(4), 532–546 (2001)
Katz, M., Shapiro, C.: Network externalities, competition, and compatibility. Am. Econ. Rev. **75**(3), 424–440 (1985)
Lee, Y.-J., Tan, Y.: Effects of different types of free trials and ratings in sampling of consumer software: An empirical study. J. Manage. Inf. Syst. **30**(3), 213–246 (2013)
Niculescu, M.F., Wu, D.J.: Economics of free under perpetual licensing: Implications for the software industry. Inf. Syst. Res. **25**(1), 173–199 (2014)
Sen, R.: A strategic analysis of competition between open source and proprietary software. J. Manage. Inf. Syst. **24**(1), 233–257 (2007)

Author Index

AlGhazi, Abulaziz 15

Bao, Zhuolan 47

Chang, Hsin-Lu 29
Chau, Michael 47
Cui, Tingru 15

Dolan, Rebecca 109

Fosso, Samuel 15

Goh, Kim Huat 1

Hu, Tianyou 79
Hung, Shin-Yuan 38

Jang, Moonkyoung 87

Kang, Tsan-Ching 38

Lee, Rumi 87
Li, Mengxiang 15
Li, Wenwen 47
Lin, Zhijie 94, 118

Shahbaznezhad, Hamidreza 109
Shen, Jun 15
Shen, Kuo-Jung 38

Tai, Jeffrey C. F. 29
Tan, Yong 94, 118
Tian, Hengqi 64
Tripathi, Arvind K. 79, 109

Wang, Kai 29
Wu, Zhenhua 94, 118

Yin, Pengzhen 47
Yoo, Byungjoon 87

Zhang, Yimiao 1
Zhao, Jing 64