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Understanding Different Cognitive Levels of Social Engagement: Evidence from Paid Q&A

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Abstract

Despite the widespread conversion of free content to paid content, empirical research investigating social engagement in the paid context still lags. Moreover, prior research used *like* and *comment* to measure social engagement without considering their differences. In this study, we conceptualize *like* and *comment* on two distinct behavioral manifestations differing cognitive processes involved: low- and high-cognitive social engagement. Specifically, setting in a paid Q&A site, we identify the answer provider characteristic (i.e., the number of followers and posts) and answer characteristic (i.e., viewership revenue) as salient factors influencing social engagement. We compare their direct and interaction effects on the two types of social engagement. Results show that identified factors have a greater direct effect and smaller interaction effect on low-cognitive social engagement than on high-cognitive social engagement. Our work advances knowledge of social engagement and has practical implications for platform practitioners to achieve social engagement.

Keywords

Social engagement, Social media, Like, Comment, Dual-process theory

1 Introduction

It is popular to develop a freelance market on social media in recent years (Yoganarasimhan 2013), especially in a post-pandemic world where many job seekers look towards the gig economy for answers (Duszynski 2020). Freelancing in America (FIA) reported that there were 57.3 million *freelancers*—self-employed individuals or groups who provide knowledge services online for exchanging money in the U.S. and estimated that the number would rise to 86.5 million by 2027 (Upwork 2017). Paid question and answer (Q&A) platform is one of the most popular freelance markets, on which freelancers provide expert advice service for a profit. Recently, it finds a viable solution on social media as many paid Q&A platforms ceased (e.g., Google Answers) (Yang and Ye 2019). On new paid Q&A, answer providers are influencers who can produce quality content and have already attracted a great number of followers. Users on social media can pay a price set by the answer provider for asking a question (askers) or pay a small flat fee set by the platform for viewing the answer to the existing question (answer viewers).

Given the fee-based access to the answer, it becomes challenging to involve users in social engagement activities on paid Q&A. The concept of social engagement is relatively less developed (Lee et al. 2018) when the majority of user-generated content (UGC) research focuses on content generation and consumption (e.g., Burtch et al. 2018; Ye and Kankanhalli 2020; Zhao et al. 2016). Social engagement refers to users' interactions with the content or other users, commonly measured by *like*, *comment*, and *share* (Khan 2017; Lee et al. 2018). Those indicators matter to evaluate the performance of UGC stakeholders, including the platform, users, and brands (Hoffman and Fodor 2010; Lipsman et al. 2012). Yet, prior literature treats *like*, *comment*, and *share* as equal or alternative measurements (Cvijikj and Michahelles 2013; Lee et al. 2018). Recent literature in marketing, psychology, and information systems (IS) has theorized that *like* and *comment* are distinct forms of social engagement, resulting from different cognitive pathways (Alhabash et al. 2019; Rossmann et al. 2016; Yang et al. 2019).

Therefore, this study is motivated to understand how users enact different social engagement behaviors that are triggered by distinct cognitive pathways. Specifically, we examine how users respond to ambient factors to implement the *like* and *comment* functions differently in the paid Q&A context.

We begin by identifying salient factors that might influence social engagement. Past research on social media found that the content creator (e.g, answer provider) and consumer's (e.g., answer viewer) performance significantly impact user behaviors (Goh et al. 2013). On social media, answer providers' performance is virtually evaluated by their capacity to attract followers and produce content, measured with follower volume and post volume separately. (Gilani et al. 2020; Harris and Rae 2011). Regarding the consumer performance, in paid Q&A, answer viewers pay to view the answer, creating the viewership revenue for each Q&A content. Viewership revenue represents the sales of Q&A content and indicates the marketing value. Thus, this study quantifies consumer performance with viewership revenue.

Furthermore, since viewership revenue is an economic indicator that remarkably reflects the financial value of the Q&A, we expect it interacts with the answer provider and viewers' performance to influence social engagement. Recently, IS literature has highlighted the importance of studying the interaction effect between characteristics of the content creator and content on social engagement (Han et al. 2020). Economic indicators have an unintended influence on user behaviors, especially in social media (e.g., Kuang et al. 2019; Zhao et al. 2016). For example, Kuang et al. (2019) found that financial reward motivates content creators to contribute both free and fee-charged content on a knowledge exchange platform, i.e., Zhihu.com. In contrast, Zhao et al. (2016) found it undermines creators' intrinsic motivations to contribute in social Q&A sites. Bapna et al. (2018) found that premium users more involve in the online music community than free users, such as listening to more songs and adding more friends. However, it is unknown how an economic indicator impacts users engaging in social engagement together with other factors.

To fill up the stated research gaps, we draw upon the dual-process theory and uses and gratification theory for answering the above research questions. The essential orientations of enacting *like* and *comment* are distinct (Yang et al. 2019; Yang et al. 2020). *Like* is a way to show attention to and interest in the existence of the content. It is more likely to be users' intuitive response to what they have observed. We term it low-cognitive social engagement. In contrast, users *commenting* on some content intends to express opinions and emotions with reasons. It is a systematic response requiring more cognitive efforts. We term it high-cognitive social engagement. Due to the different cognitive processes, people enacting low-cognitive social engagement might demand and respond to pertinent factors differently from those enacting high-cognitive social engagement. For example, people give a *like* more automatically than posting a *comment*. Thus, complicated situations, e.g., interactions between the content creator and content characteristics, are less likely to trigger or change the low-cognitive social engagement.

We leveraged panel data downloaded from a paid Q&A site, Weibo Q&A, and conducted multiple regression models to test our hypotheses. Results suggest that an answer provider's follower volume and post volume and the Q&A's viewership revenue have a significantly greater impact on users' low- than high-cognitive social engagement. Second, the viewership revenue strengthens the positive influence of an answer provider's follower volume on users' social engagement but weakens the negative impact of an answerer's post volume. Third, the interplay impacts described before are significantly greater for high-cognitive social engagement than for low-cognitive social engagement. Our findings contribute to understanding distinct forms of social engagement and their antecedents in the paid context.

The rest of this paper proceeds as follows. In the following sections, we review the related work in user engagement on social media, introduce the dual-process theory and uses and gratification theory as our theoretical foundation, and develop our research hypotheses. We then describe the research context and report the details of our data, followed by econometric models and corresponding estimation results. Finally, we conclude a discussion of the implications of our findings to research and practice.

2 Theoretical Background and Hypotheses

2.1 Online Social Engagement

With the growing prevalence of social media, both practitioners and scholars paid much attention to social engagement (Hoffman and Fodor 2010; Lee et al. 2018). In the existing literature, social engagement is a sweeping notion of users' various behaviors in online communities, including content generation, social interaction, and content consumption (Bapna et al. 2018). While most research on social engagement focuses on exploring the antecedents and consequences of content generation and consumption behaviors (e.g., Khan 2017; Kuang et al. 2019), the underlying mechanism of social interaction behaviors is relatively less investigated (Yang et al. 2019).

Regarding the perspective of social interaction, engagement refers to "the intensity of an individual's participation in and connection with" the content and content creators (Vivek et al. 2012, p. 133). Thus, for avoiding ambiguity, this study explicitly defines social engagement as users' social interaction behaviors that are manifested by *likes*, *comments*, and *shares* in social networks (Rossmann et al. 2016). This type of social engagement plays a central role in evaluating UGC. Prior research suggests that social interactions between content creators and consumers can boost information value for content (Ruth 2012) so that other users can assess the quality and popularity of the content (Majchrzak et al. 2013), which further catalyze some unpredicted economic benefits (Raban 2009).

Despite the practical importance, there is a fundamental vagueness about how factors influencing users' social engagement in a specific context (Maslowska et al. 2016), especially in terms of distinct forms of social engagement (Yang et al. 2019). In paid Q&A, answer providers build up personal brands (Brems et al. 2017) and market their self-generated products (i.e., paid Q&A) (Khurana et al. 2019). One paid Q&A resembles a segment of the answer provider's brand community. Answer viewers create additional information and economic value for the paid answer through contributing to viewership revenue (Majchrzak et al. 2013; Ruth 2012). Prior literature on brand community suggests that marketer-performance (e.g., an answerer's follower volume and post volume) and consumer-performance (i.e., viewership revenue) are two sources of salient drivers in community members' behaviors (Goh et al. 2013). Recent studies further note that social media users' actions are more complicated (Hoang and Lim 2012) than being independently impacted by one source of characteristics, such as users' and items' (Han et al. 2020). This study expects to find significant interactions between the answer provider characteristics (i.e., follower volume and post volume) and the Q&A's economic feature (i.e., viewership revenue) in users' social engagement. Thus, we hypothesize

H1: An answer provider's follower volume has an interaction effect with the Q&A's viewership revenue on users' (a) low-cognitive social engagement and (b) high-cognitive social engagement.

H2a: An answer provider's post volume has an interaction effect with the Q&A's viewership revenue on users' (2) low-cognitive social engagement and (b) high-cognitive social engagement.

Furthermore, low-cognitive social engagement (i.e., *like*) and high-cognitive social engagement (i.e., *comment*) are two conceptually distinct forms of social engagement (Rossmann et al. 2016; Yang et al. 2019). The next section will provide theoretical reasoning behind the two forms of social engagement and propose relevant research hypotheses.

2.2 Dual-process Theory

The dual-process paradigm originated from the psychology of reasoning in the 1970s (Wason and Evans 1974) and has evolved into broad dual-process theories, such as the heuristic-systematic model and the elaboration likelihood model. The fundamental assumption of dual-process theories is that people process information in two ways: intuitively and systematically. The former way is habitual and heuristic, whereas the latter is reflective and circumspective (Evans and Stanovich 2013). Consequently, distinct cognitive processes lead to differentiated responses when various responses are optional.

Social engagement is the behavioral manifestation of individuals' psychophysiological responses (Alhabash et al. 2019). IS literature has documented that *like* and *comment* are two levels of involvement with the content in terms of requiring a different amount of cognitive effort (Yang et al. 2019). *Like* is a "lightweight, one-click feedback action" (Scissors et al. 2016), whereas *comment* is the result of deliberate cognitive processes including information decoding, encoding, and delivering (Alhabash et al. 2019). Drawing insights from the dual-process theory, we conceptualize *like* as an intuitive behavioral manifestation, namely low-cognitive social engagement, and *comment* as a systematic behavioral manifestation, namely high-cognitive social engagement.

Compared to low-cognitive social engagement, high-cognitive social engagement requires more cognitive effort to comprehend pertinent factors and complete the comment task (Alhabash et al. 2019). One user likes a paid Q&A for showing attention and interest to the question topic or support the answerer and/or answer. However, if a user intends to comment on a paid Q&A, s/he would experience a reflective process of thinking over what s/he reads and wants to write down. In the modern media environment, e.g., social media, people are facing overloaded information. They habitually use visible and salient cues for superficial judgments (Lee and Pingree 2016). Thus, intuitive processing would initially outrank systematic processing, which triggers users' low-cognitive social engagement. Moreover, as cognitive processes stepping forward, their attention to the indicators' additional value will decrease due to the limited cognition capacity (Ferran and Watts 2008). Hence, we expect the aforementioned salient factors to be more influential for low- than high-cognitive social engagement:

H3: An answer provider's (a) follower volume and (b) post volume have a greater impact on low-cognitive social engagement than on high-cognitive social engagement.

H4: The Q&A's viewership revenue has a greater impact on low-cognitive social engagement than on high-cognitive social engagement.

2.3 Uses and Gratification Theory

Uses and gratification theory is a fruitful approach for understanding individual behavior from the perspective of motivations (Eighmey and McCord 1998). It was developed to study the effectiveness of the radio medium in attracting and holding audiences. And then, it is gradually employed to explore why people adopt and use various forms of media, including newspapers (Wimmer and Dominick 1994), television and electronic bulletins (Rubin 1981), and modern new media such as the Internet and social media (Leung 2009). The term, gratification, indicates that the selected media satisfies individual needs in attaining information, entertainment, social, and remuneration (Ko et al. 2005).

With the rapid growth of social media that is engineered to fulfill the above needs, uses and gratification theory provides a valuable theoretical lens for interpreting users' social engagement with media content (Dolan et al. 2016). Prior research has linked various gratifications to social media users' content seeking and consumption (Malthouse et al. 2013; Smock et al. 2011). Yet, how they motivate users to enact distinct forms of social engagement lacks explicit recognition.

Integrating the uses and gratification theory with dual-process theory, we posit that the interplay between characteristics of the content creator and content has a greater impact on high-cognitive social engagement than on low-cognitive social engagement. Users enacting low-cognitive social engagement experiences a heuristic process and demands little motivation. Either answer provider characteristics or answer characteristics are sufficient to attract users to give a one-click *like*. However, both the psychological and physiological procedures in proceeding high-cognitive social engagement are much more complicated (Alhabash et al. 2019). Before submitting a *comment*, they keep decoding and encoding ambient information interactively and collectively. Therefore, we expect

H5a: The interaction effect between an answer provider's follower volume and the Q&A's viewership revenue is smaller on low-cognitive social engagement than on high-cognitive social engagement.

H5b: The interaction effect between an answer provider's post volume and the Q&A's viewership revenue is smaller on low-cognitive social engagement than on high-cognitive social engagement.

3 Methodology

3.1 Research Setting and Data

We used secondary data from Weibo Q&A. At the end of 2016, Sina Weibo, China's second-largest social media platform, launched the paid Q&A service and named it Weibo Q&A. The format of one Q&A published on Weibo Q&A is the same as a tweet on Weibo, consisting of the answer provider's (publisher) account name, answering time (publishing time), Q&A detail (tweet content), and social interaction icons (e.g., like, comment, and share). The Q&A detail contains the tweet content, question content, question price that the asker pays to the answer provider, and the real-time viewership of the answer to the question. Figure 2 shows an actual paid Q&A from Weibo Q&A with the translation.

1. Answer Provider: 褚明宇
2. Answering Date: 18th May 16:35
3. Tweet content: I answered @longren,,,,'s question, the question price is ¥2198.00. Everyone come and view the answer with RMB 1~
4. Question content: Jack Ma was criticized because he said "commerce is the finest public service" during the annual public service award ceremony of Alibaba. I want to hear from your opinion.
5. Real-time viewership and question price: 4924 people viewed the answer, the question price is ¥2198.00
6. Social engagement: 109 shares, 51 comments, and 193 likes

Figure 2. Screenshot and translation of an actual Q&A

We built a software tool in Python to connect with Sina Weibo's Graph API to download data. To ensure that the downloaded data are related to paid Q&As, the Python-based scrapy searches tweets that are framed in the format of "I answered @" (see Figure 2). The collected data set consists of the answer provider and asker's profile data, as well as Q&A relevant data. We started the data collection work on 2nd Aug 2019 and ended on 1st Oct 2019. The scrapy worked in the early morning of Beijing time every day. We deleted three types of Q&A from our sample: 1) free Q&As as this study focuses on paid Q&As; 2) Q&As that were tracked less than five times that is usually the minimum requirement for panel regression; 3) Q&As with missing data of dependent, independent, and control variables. Finally, we reserved 2,053 unique Q&As, giving us unbalanced panel data with 12,911 Q&A-day observations for analysis. The large panel size helps us control for unobservable effects and relax some parametric assumptions for inference.

3.2 Variable Measurement

The key dependent variables in our empirical analysis are audiences' low- and high-cognitive social engagement, which is measured with the accumulated *like volume* and *comment volume* the *i*'s paid Q&A receives at time *t*, i.e., $Like_{it}$ and $Comment_{it}$. Our key independent variables are answerer characteristics and the paid Q&A's economic characteristic. We operationalized them with the accumulated number of the *i*'s answerer's followers and posts, and the accrued viewership revenue of the *i*'s paid Q&A till time *t*, i.e., $Follower_{it}$, $Post_{it}$, and $Viewership_{it}$, respectively. On Weibo Q&A, people who want to view the answer are all required to pay RMB 1. Thus, the viewership can directly measure the viewership revenue of each paid Q&A.

We also included several control variables. First, answer providers' other characteristics might impact users' social engagement, including the following volume ($following_{it}$), gender ($Gender_i$), whether s/he is fully self-employed ($Self\text{-}employed_i$). In detail, following is one type of social connections. Users are more likely to interact with users within their networks. Thus, following a greater number of users may attract more users engage in his/er content. An answer provider who is not fully self-employed should work in an offline company, then his/er offline influential power may take effect online.

Second, similar to the answer provider, the asker also contributes to the Q&A. Thus, the asker's characteristics might also influence users to interact with the content. An asker's characteristics include follower volume (A$follower_{it}$), following volume (A$following_{it}$), post volume ($Apost_{it}$), gender ($Agender_i$), and whether s/he has a certification from Weibo ($Acertified_i$). Third, other content characteristics, including whether the paid Q&A is published during office hours or not ($Office\_hour_i$), the topic ($Topic_i$), and the question price ($Price_i$), might impact the dependent variables. For instance, if a paid Q&A is published during office hours, people may not take care of it. Then, there would be fewer people engage in this content than that published during off-hours.

We created dummy variables for categorical variables (see Table A1 in Appendix). The descriptive information for continuous variables is listed in Table 1, and the correlation values are shown in Table 2. Since the correlation coefficients among *Like*, *Comment*, and *share* are extremely high, we do not include the other two as control variables when conducting estimations.

Variables	Mean	SD	Min	Max	Observations
$Like_{it}$	24.15	175.36	0	4306	12911
$Comment_{it}$	9.54	51.19	0	1286	12911
$Share_{it}$	8.47	52.95	0	1120	12911
$Follower_{it}$	1347393	2060494	502	14600000	12911
$Posts_{it}$	33114.9	35140.41	52	190950	12911
$Viewership_{it}$	213.08	596.46	0	16372	12911
$Following_{it}$	1200.79	1640.77	0	11409	12911
A$follower_{it}$	31094.38	346377.1	0	8374264	12911
A$following_{it}$	1808.8	3600.12	0	5113	12911
$Aposts_{it}$	328.02	529.28	0	7221	12911
$Price_i$	143.41	462.75	0	10000	12911

Table 1. Variable Description and Statistics

Variables	1	2	3	4	5	6	7	8	9	10	11
1. Like	1										
2. Comment	.91	1									
3. Share	.94	.92	1								
4. Follower	.08	.06	.08	1							
5. Posts	-.03	-.06	.02	.42	1						
6. Viewership	.34	.23	32	.11	.05	1					
7. Following	-.05	-.06	-.05	-.01	.27	-.09	1				
8. Afollower	-.01	-.01	.00	0.02	-.02	-.00	-.02	1			
9. Afollowing	-.02	-.02	-.00	.09	.19	.01	.08	.28	1		
10. Aposts	-.02	-.02	-.01	.04	.04	-.00	.06	.11	.39	1	
11. Price	.05	.03	.06	.04	.08	.22	-.02	.00	.10	.04	1

Table 2. Correlations

3.3 Model Estimation

We tested the proposed hypotheses with a panel data set, because the panel regression model can mitigate the collinearity problem among independent variables (Hsiao 2014). Since we have time-invariant variables (e.g., price, answering time, answerer gender, question topic, etc.) in estimation models, we estimated random effects panel models (REPM) of our dependent variables (Bell and Jones

2015). Given the data skewness, we have log-transformed all countable variables and added one to each variable for avoiding the problem caused by log of zero (Budge et al. 2010). The normality test on the log-transformed data shows a normal distribution of residuals. The subscript i in the equation represent the Q&A, and subscript t represents the time point. We estimate the following panel data model:

$$Log(Like_{i,t}+1) = \beta_1 \, log(Followers_{i,t}+1) + \beta_2 \log(Post_{i,t}+1) + \beta_3 \log(Viewership_{i,t}) + \beta_4 \log(Follower_{i,t}+1) * \log(Viewership_{i,t}+1) + \beta_5 \log(Post_{i,t}+1) * \log(Viewership_{i,t}+1) + \beta_6 Controls_{i,t} + \mathcal{E}_i \quad (1)$$

$$Log(Comment_{i,t}+1) = \beta_1 \, log(Followers_{i,t}+1) + \beta_2 \log(Post_{i,t}+1) + \beta_3 \log(Viewership_{i,t}) + \beta_4 \log(Follower_{i,t}+1) * \log(Viewership_{i,t}+1) + \beta_5 \log(Post_{i,t}+1) * \log(Viewership_{i,t}+1) + \beta_6 Controls_{i,t} + \mathcal{E}_i \quad (2)$$

4 Data Analysis and Results

4.1 Hypotheses Testing

Variable	DV = $Like_{i,t}$			DV = $Comment_{i,t}$		
	a1	a2	a3	b1	b2	b3
$Follower_{it}$		.23(.01)***	.26(.01)***		.16(.01)***	.20(.01)***
$Post_{it}$		-.19(.02)***	-.23(.02)***		-.17(.02)***	-.23(.02)***
$Viewership_{it}$		.39(.01)***	.38(.01)***		.31(.01)***	.29(.01)***
$Viewership_{it}$* $Follower_{it}$			.10(.02)***			.11(.02)***
$Viewership_{it}$* $Post_{it}$			-.24(.02)***			-.28(.01)***
$Price_i$	.23(.02)***	.01(.01)	.00(.01)	.15(.02)***	-.01(.02)	-.02(.02)
$Following_{it}$	-.12(.02)***	-.01(.01)	-.02(.01)	-.03(.02)	.08(.01)***	.07(.01)***
A$follower_{it}$	-.06(.01)***	-.02(.01)	-.02(.01)*	-.02(.01)*	.00(.01)	.00(.01)
$Apost_{it}$	.02(.01)*	.03(.01)***	.03(.01)***	-.01(.01)	-.01(.01)	-.01(.01)
A$following_{it}$	.03(.01)*	-.01(.01)	-.01(.01)	.03(.01)**	.01(.01)	.01(.01)
$Gender_i$ = female	-.23(.07)**	.00(.05)	.01(.05)	-.18(.07)**	.01(.05)	.02(.05)
$Agender_i$ = female	-.05(.05)	.01(.04)	.01(.04)	.05(.05)	.10(.04)**	.10(.04)*
$Acertified_i$ = No	-.20(.11)	-.14(.08)	-.17(.08)*	.05(.10)	.06(.08)	.03(.08)
$Office\_hour_i$ = Yes	-.21(.05)***	-.01(.04)*	-.09(.04)*	-.13(.05)*	-.04(.04)	-.03(.04)
$Self\text{-}employed_i$ = Yes	-.63(.06)***	.09(.04)***	-.01(.04)	-.55(.06)***	-.06(.05)	-.06(.05)
constant	2.39(.68)	.06(.50)	.09(.49)	1.17(.65)	-.31(.53)	-.22(.52)
R2	0.3776	0.6444	0.6785	0.2262	0.5439	0.5514
Obs.	12,881					

a. for interactive variables, each variable is mean-centered before multiplication
b. dummy variables for $Topic_i$ are included to all models but not reported for brevity
c. significance level: *p <0.05; **p <0.01; ***p <0.001.

Table 3. Data Analysis Result

We incrementally added control variables, main effect variables, and interactive effect variables in Model 1, 2, and 3. Results in Table 3 show the data analysis of hypotheses 1 and 2. In Table 3, the results of the main effects in Model a2 and b2 are largely similar to them in Model a3 and b3, accordingly. This suggests our results are robust across estimation methods. As shown in Model a3 and b3, viewership has significant interaction effects with both followers and posts on both like and comment. Thus, our hypotheses H1a, H1b, H2a, and H2b are all supported. Then, following Keil et al. (2000), we statistically compared the corresponding regression coefficients from Model a3 and b3 of Table 3 and computed the T-values shown in Table 4. From the coefficient differences and T-values, it can be seen that all the comparison hypotheses (H3a, H3b, H4, H5a, and H5b) are supported.

Variable	$Like_{i,t}$ *VS.* $Comment_{i,t}$		
	S_{pooled}	$\Delta\|\beta\|$ T-test	Results
$Follower_{it}$	0.012	0.06 ***	H3a supported
$Post_{it}$	0.018	0.00*	H3b supported
$Viewership_{it}$	0.007	0.08 ***	H4 supported
$Viewership_{it} * Follower_{it}$	0.016	-0.01***	H5a supported
$Viewership_{it} * Post_{it}$	0.015	-0.05***	H5b supported
a. significance level: *p<0.05; **p<0.01; ***p <0.001			

Table 4. The Comparison of Low and High-cognitive social engagement

4.2 Robustness Check

To test the robustness of our results, we have estimated our models with robust standard errors clustered by answer providers. Results are shown in Table5 and consistent with previous main analyses.

Variable	DV= $Likes_{i,t}$	DV= $Comments_{i,t}$	Likes *VS.* Shares		
			S_{pooled}	$\Delta\|\beta\|$ T-test	Results
$Follower_{it}$	.26(.06)***	.20(.05)***	0.056	0.06 ***	Consistent
$Post_{it}$	-.23(.07)***	-.23(.05)***	0.059	0.00***	Consistent
$Viewership_{it}$	.38(.04)***	.29(04)***	0.038	0.08 ***	Consistent
$Viewership_{it} * Follower_{it}$	.01(.13)	.11(.12)	0.124	-0.01**	Consistent
$Viewership_{it} * Post_{it}$	-.24(.13)*	-.28(.13)*	0.128	-0.05*	Consistent
a. significance level: *p<0.05; **p<0.01; ***p <0.001					

Table 5. Robustness Check

5 Discussion

In this paper, we set out to answer two research questions: (1) How do the answerer's characteristics and the answer's economic feature affect users' social engagement with the paid Q&A? (2) Are there significant differences between the impacts of answer provider and answer's characteristics on the low- and high-cognitive social engagement? We have three key sets of findings. First, we identify and examine that an answerer's follower volume and the paid Q&A's viewership revenue have a positive influence on social engagement, but the answerer's post volume has a negative impact. On social media, individuals are habitually interested in the content published by popular users who have a huge number of followers (Goes et al. 2014) or consumed by many peer users (the viewership revenue in this study) (Gächter et al. 2013). However, an increasing number of optional content, such as that the same user posts many messages, could automatically distract audiences' attention (Drover et al. 2018).

Second, we theorize that *like* and *comment* are two different levels of social engagement. In detail, *like* is a lower level of social engagement that users enact with an intuitive cognition, whereas *comment* is a higher level of engagement requiring a systematic cognition. With an empirical analysis, we indeed find that the impacts of answerer and answer characteristics are greater for low- than high-cognitive social engagement. These results examined that salient factors relevant to the paid Q&A or its provider drive more users to proceed with low-cognitive social engagement. Third, we demonstrate that interactions between answerer and answer characteristics have a greater impact on high- than low-cognitive social engagement. Users who are oriented to posting comments demand greater motivation for enacting it. They evaluate pertinent information from different sources more comprehensively.

This study contributes to the literature in three ways. First, our research contributes to one stream of UGC literature, which seeks to uncover drivers of social engagement, especially in a new context, i.e., paid Q&A in this study. Second, our work extends prior studies on theorizing different social engagement behaviors (Alhabash et al. 2019; Yang et al. 2019) and is the first to empirically differentiate the impacts of content and content creator characteristics on different cognitive levels of social engagement. Finally, our work adds to the IS literature that examines the interaction effect between financial factors and content/content creator characteristics on user behaviors.

Our research also has important implications for practice. First, for users who want to commercialize content but are concerned that this may reduce audiences' social engagement, they should be assured that their social status would help them retain and involve users. However, they might be cautioned to avoid posting messages too frequently as it would lead to reduced social engagement. It is worthwhile to produce popular paid content, which not only increases their profit but also acts as a salient cue driving users to engage in social interactions and catching other users' attention to the paid content than free content. Second, in looking at the different intensity of the impacts, content providers and social media marketing practitioners can have specific goals for gaining more likes or comments and be aware of the trade-offs between the two distinct outcomes. For example, companies valuing the high level of engagement with the content should gauge the marketing performance with comment volume.

This study has several limitations. First, we conduct our research with data from one social network. In the future, researchers can replicate the model and methods in other social networks. Second, although this study includes as many as observable variables into the estimation, there is a need to understand the impacts of semantic and sentiment characteristics of the paid content. Also, in this study, we conceptualize the different cognitive levels of social engagement with the number of likes and comment that one paid Q&A receives. Future studies may attempt to theorize the social engagement levels of the share volume and comment divided by semantic features and differentiate them with like and comment volumes. Third, future research may seek to investigate the differential social interactions in free versus paid social networks. To conclude, this study is an important step toward exploring the antecedents of social engagement in the paid context and understanding the distinct forms of social engagement.

6 References

Alhabash, S., Almutairi, N., Lou, C., and Kim, W. 2019. "Pathways to Virality: Psychophysiological Responses Preceding Likes, Shares, Comments, and Status Updates on Facebook," *Media Psychology* (22:2), pp. 196-216.

Bapna, R., Ramaprasad, J., and Umyarov, A. 2018. "Monetizing Freemium Communities: Does Paying for Premium Increase Social Engagement?," *MIS Quarterly* (42:3), pp. 719-735.

Bell, A., and Jones, K. 2015. "Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data," *Political Science Research and Methods* (3:1), pp. 133-153.

Brems, C., Temmerman, M., Graham, T., and Broersma, M. 2017. "Personal Branding on Twitter: How Employed and Freelance Journalists Stage Themselves on Social Media," *Digital Journalism* (5:4), pp. 443-459.

Budge, S., Ingolfsson, A., and Zerom, D. 2010. "Empirical Analysis of Ambulance Travel Times: The Case of Calgary Emergency Medical Services," *Management Science* (56:4), pp. 716-723.

Burtch, G., Hong, Y., Bapna, R., and Griskevicius, V. 2018. "Stimulating Online Reviews by Combining Financial Incentives and Social Norms," *Management Science* (64:5), pp. 2065-2082.

Cvijikj, I. P., and Michahelles, F. 2013. "Online Engagement Factors on Facebook Brand Pages," *Social network analysis mining* (3:4), pp. 843-861.

Dolan, R., Conduit, J., Fahy, J., and Goodman, S. 2016. "Social Media Engagement Behaviour: A Uses and Gratifications Perspective," *Journal of Strategic Marketing* (24:3-4), pp. 261-277.

Drover, W., Wood, M. S., and Corbett, A. C. 2018. "Toward a Cognitive View of Signalling Theory: Individual Attention and Signal Set Interpretation," *Journal of Management Studies* (55:2), pp. 209-231.

Duszynski, M. 2020. "Gig Economy: Definition, Statistics & Trends [2020 Update]." Retrieved 26th May, 2020, from https://zety.com/blog/gig-economy-statistics?gclid=CjwKCAjw2a32BRBXEiwAUcugiCxb9NG_WOoeZdW0P-epAOpZR-TAyZhchnMgRAasiO2Bymgh32y1QBoCFZ0QAvD_BwE

Eighmey, J., and McCord, L. J. J. o. b. r. 1998. "Adding Value in the Information Age: Uses and Gratifications of Sites on the World Wide Web," (41:3), pp. 187-194.

Evans, J. S. B., and Stanovich, K. E. 2013. "Dual-Process Theories of Higher Cognition: Advancing the Debate," *Perspectives on psychological science* (8:3), pp. 223-241.

Ferran, C., and Watts, S. 2008. "Videoconferencing in the Field: A Heuristic Processing Model," *Management science* (54:9), pp. 1565-1578.

Gächter, S., Nosenzo, D., and Sefton, M. 2013. "Peer Effects in Pro-Social Behavior: Social Norms or Social Preferences?," *Journal of the European Economic Association* (11:3), pp. 548-573.

Gilani, P., Bolat, E., Nordberg, D., and Wilkin, C. 2020. "Mirror, Mirror on the Wall: Shifting Leader–Follower Power Dynamics in a Social Media Context," *Leadership* (16:3), pp. 343-363.

Goes, P. B., Lin, M., and Au Yeung, C.-m. 2014. "“Popularity Effect” in User-Generated Content: Evidence from Online Product Reviews," *Information Systems Research* (25:2), pp. 222-238.

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

Han, Y., Lappas, T., and Sabnis, G. 2020. "The Importance of Interactions between Content Characteristics and Creator Characteristics for Studying Virality in Social Media," *Information Systems Research* (31:2), pp. 576-588.

Harris, L., and Rae, A. 2011. "Building a Personal Brand through Social Networking," *Journal of Business Strategy* (32:5), pp. 14-21.

Hoang, T.-A., and Lim, E. P. 2012. "Virality and Susceptibility in Information Diffusions," in *Sixth International Conference on Weblogs and Social Media*, Palo Alto, CA: AAAI Press, pp. 146-153.

Hoffman, D. L., and Fodor, M. 2010. "Can You Measure the Roi of Your Social Media Marketing?," *MIT Sloan Management Review* (52:1), pp. 40-50.

Hsiao, C. 2014. *Analysis of Panel Data*. Cambridge: Cambridge University Press.

Keil, M., Tan, B. C., Wei, K.-K., Saarinen, T., Tuunainen, V., and Wassenaar, A. 2000. "A Cross-Cultural Study on Escalation of Commitment Behavior in Software Projects," *MIS Quarterly* (24:2), pp. 299-325.

Khan, M. L. 2017. "Social Media Engagement: What Motivates User Participation and Consumption on Youtube?," *Computers in Human Behavior* (66), pp. 236-247.

Khurana, S., Qiu, L., and Kumar, S. 2019. "When a Doctor Knows, It Shows: An Empirical Analysis of Doctors’ Responses in a Q&a Forum of an Online Healthcare Portal," *Information Systems Research* (30:3), pp. 872-891.

Ko, H., Cho, C.-H., and Roberts, M. S. 2005. "Internet Uses and Gratifications: A Structural Equation Model of Interactive Advertising," *Journal of advertising* (34:2), pp. 57-70.

Kuang, L., Huang, N., Hong, Y., and Yan, Z. 2019. "Spillover Effects of Financial Incentives on Non-Incentivized User Engagement: Evidence from an Online Knowledge Exchange Platform," *Journal of Management Information Systems* (36:1), pp. 289-320.

Lee, D., Hosanagar, K., and Nair, H. S. 2018. "Advertising Content and Consumer Engagement on Social Media: Evidence from Facebook," *Management Science* (64:11), pp. 5105-5131.

Lee, J., and Pingree, R. J. 2016. "Cues About Cues in Political Comments on Social Media: Effects of Commenters' Attractiveness and Claims of Cognitive Effort," *The Journal of Social Media in Society* (5:3), pp. 92-120.

Leung, L. 2009. "User-Generated Content on the Internet: An Examination of Gratifications, Civic Engagement and Psychological Empowerment," *New media & society* (11:8), pp. 1327-1347.

Lipsman, A., Mudd, G., Rich, M., and Bruich, S. 2012. "The Power of "Like": How Brands Reach (and Influence) Fans through Social-Media Marketing," *Journal of Advertising research* (52:1), pp. 40-52.

Majchrzak, A., Faraj, S., Kane, G. C., and Azad, B. 2013. "The Contradictory Influence of Social Media Affordances on Online Communal Knowledge Sharing," *Journal of Computer-Mediated Communication* (19:1), pp. 38-55.

Malthouse, E. C., Haenlein, M., Skiera, B., Wege, E., and Zhang, M. 2013. "Managing Customer Relationships in the Social Media Era: Introducing the Social Crm House," *Journal of interactive marketing* (27:4), pp. 270-280.

Maslowska, E., Malthouse, E. C., and Collinger, T. 2016. "The Customer Engagement Ecosystem," *Journal of Marketing Management* (32:5-6), pp. 469-501.

Raban, D. R. 2009. "Self-Presentation and the Value of Information in Q&a Websites," *Journal of the American society for information science and technology* (60:12), pp. 2465-2473.

Rossmann, A., Ranjan, K. R., and Sugathan, P. 2016. "Drivers of User Engagement in Ewom Communication," *Journal of Services Marketing* (30:5), pp. 541-553.

Rubin, A. M. 1981. "An Examination of Television Viewing Motivations," *Communication research* (8:2), pp. 141-165.

Ruth, R. D. 2012. "Conversation as a Source of Satisfaction and Continuance in a Question-and-Answer Site," *European Journal of Information Systems* (21:4), pp. 427-437.

Scissors, L., Burke, M., and Wengrovitz, S. 2016. "What's in a Like? Attitudes and Behaviors around Receiving Likes on Facebook," in *Proceedings of the 19th acm conference on computer-supported cooperative work & social computing*, CA: SAN FRANCISCO, pp. 1501-1510.

Smock, A. D., Ellison, N. B., Lampe, C., and Wohn, D. Y. 2011. "Facebook as a Toolkit: A Uses and Gratification Approach to Unbundling Feature Use," *Computers in human behavior* (27:6), pp. 2322-2329.

Upwork. 2017. "Freelancers Predicted to Become the U.S. Workforce Majority within a Decade, with Nearly 50% of Millennial Workers Already Freelancing, Annual "Freelancing in America" Study Finds." Retrieved 26th May, 2020, from https://www.upwork.com/press/2017/10/17/freelancing-in-america-2017/

Vivek, S. D., Beatty, S. E., and Morgan, R. M. 2012. "Customer Engagement: Exploring Customer Relationships Beyond Purchase," *Journal of marketing theory and practice* (20:2), pp. 122-146.

Wason, P. C., and Evans, J. S. B. 1974. "Dual Processes in Reasoning?," *Cognition* (3:2), pp. 141-154.

Wimmer, R. D., and Dominick, J. R. 1994. "Mass Media Research: An Introduction ". California: Wadsworth.

Yang, M., Ren, Y., and Adomavicius, G. 2019. "Understanding User-Generated Content and Customer Engagement on Facebook Business Pages," *Information Systems Research* (30:3), pp. 839-855.

Yang, M., Ren, Y. C., and Adomavicius, G. 2020. "Engagement by Design: An Empirical Study of the “Reactions” Feature on Facebook Business Pages," *ACM Transactions on Computer-Human Interaction* (Forthcoming).

Yang, X., and Ye, H. J. 2019. "Commercialized Content on Social Media Platforms: Exploring the Drivers of the Viewership of Paid Q&A," in *Proceedings of the 52nd Hawaii International Conference on System Sciences*, Hawaii: AIS, pp. 2709-2718.

Ye, H. J., and Kankanhalli, A. 2020. "Value Cocreation for Service Innovation: Examining the Relationships between Service Innovativeness, Customer Participation, and Mobile App Performance," *Journal of the Association for Information Systems* (21:2), pp. 292-311.

Yoganarasimhan, H. 2013. "The Value of Reputation in an Online Freelance Marketplace," *Marketing Science* (32:6), pp. 860-891.

Zhao, L., Detlor, B., and Connelly, C. E. 2016. "Sharing Knowledge in Social Q&a Sites: The Unintended Consequences of Extrinsic Motivation," *Journal of Management Information Systems* (33:1), pp. 70-100.

Appendix 1

Topic	Tag	Obs.
Aesthetic design and art	1	109
Car and digital game	2	140
Education and parenting	3	922
Travel and photography	4	200
History and military affaire	5	256
Fashion and beauty	6	126
Finance and economics	7	3184
Sport and fitness	8	162
Digital and IT	9	514
Popular science	10	172
Constellatio	11	355
Social focus	12	2682
Healthcare	13	2075
Law	14	684
Pop culture (music, movie, drama, variety show, idol, cartoon)	15	1070
others	16	260

Gender	Tag	Obs.
Female	1	2478
Male	2	10403

Agender	Tag	Obs.
Female	1	5857
Male	2	7054

Answering	Tag	Obs.
Off hour	1	8401
Office hour	2	4510

Self_employed	Tag	Obs.
No	1	4055
Yes	2	8856

Acertified	Tag	Obs.
No	1	12007
Yes	2	904

Table A1. Categories of Categorical Variables