THREE ESSAYS ON PAID Q&A: UNDERSTANDING CONTENT CONSUMPTION AND SOCIAL ENGAGEMENT

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ABSTRACT

Social media has been widely used as a channel to catch up with real-time occurrences in the globe and keep connected with social ties. Practitioners have also been aware of its economic potential and designed various digital business models to monetize user-generated content (UGC) on social media, such as advertising revenue model, premium subscription model, and pay-per-item model. Paid question and answer (Q&A) is a novel pay-per-item model, empowering influential users to profit from answering users' personalized questions. Recently, an increasing number of social media platforms have launched paid Q&A services, such as Fenda, Weibo Q&A, and Zhihu Paid Consultation.

On paid Q&A, the platform authorizes influential users, who long perform well in creating quality content, to become answerers. A user (asker) nominates an answerer to answer his/her question and prepays a price (known as question price) that the answerer sets. Once the answerer responds to the question, the question with a paid link to the answer will be automatically published on the answerers' homepage and appear in the followers' Home timelines. Users (answer viewers) who are interested in the question and answer can pay a small flat fee to view the answer to the question (viewership). All users can interact with each piece of published Q&A through tapping the like, share, and comment icons. One piece of paid Q&A has the same format as general posts in social media. Unlike previous monetization models, paid Q&A charges a nominal flat fee for viewership. More uniquely, the asker can share the proceeds of the viewership with the answerer.

This novel business model challenges the prior literature on UGC and user engagement due to the uniqueness of paid Q&A in the content creation and consumption ways and the economic incentive. First, the majority of the existing research focuses on the free context. A few studies

that investigate user engagement in the paid context (e.g., paid news in New York Times and paid music in Last.fm) are insufficient for us to understand certain users' behavioral mechanisms in the paid Q&A context. It is even rare to see that prior Q&A studies conduct their research from an economic perspective. Second, existing literature has examined many financial and social factors influencing content creators' (i.e., answerer) contribution behavior, while limited research explores antecedents of content consumers' payment and interaction behaviors. Therefore, this thesis, based on the paid Q&A context, addresses knowledge gaps regarding three contextual but representative users, (1) answer viewers: what factors drive viewers to pay for answers? (2) askers: how can askers frame profitable questions? (3) social interaction users: whether users perform different social interactions (e.g., like and comment) via distinct cognitive ways?

This thesis conducted three empirical studies to fill up the three research gaps. Drawing upon the signaling theory and previous related literature, study 1 developed a model to examine the direct and interaction effects of social and economic signals on the paid answer viewership. Based on the social presence theory and previous related literature, study 2 developed a model to examine the relationships between linguistic features of the question content and an asker's profit. Study 3 employed the dual-process theory, uses and gratification theory, and previous related literature to develop a model for examining whether users give likes and comments differently when reacting to the answerer and answer's characteristics.

The three research models were tested by secondary data collected from Weibo Q&A. Weibo Q&A is a paid Q&A service launched by Sina Weibo, one of China's largest social media platforms. Regression models were used to analyze the data and test hypotheses in three models. Study 1 found that the answerer's social media status (i.e., membership level) and social media

popularity (e.g., follower volume) as well as the Q&A's social favor (i.e., like volume), diffusion (i.e., sharing volume), and feedback (i.e., comment volume) positively impact the paid answer viewership. Besides, results suggest that question price enhances the impacts of social media status, social favor, and social diffusion on the paid answer viewership. However, question price weakens the effects of social media popularity and social feedback. Study 2 found that the question informativeness has an inverted U effect on an askers' profit from one question, and the sentiment extremity reflected by the question content increases the askers' profit. Study 3 found that the question price and answerer's social media popularity and voluntary contributions (i.e., free post volume) significantly influence social engagement, i.e., likes and comments. Further, their direct effects are significantly greater on the low-cognitive social engagement, i.e., likes. In contrast, the interaction effects between the question price and the answerer's characteristics are stronger on the high-cognitive social engagement, i.e., comments. Theoretical and management implications, limitations, and future research are discussed in each study separately. Finally, this thesis offers a conclusion by summarizing findings and contributions.

Dedicated to the memory of my grandfather

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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Certification by Co-Authors

The undersigned hereby certify that:

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CO-AUTHORS

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Dr Xinwei Wang	Edited manuscript
Dr Jonathan Hua Ye	Suggested improvements to the conceptual structure, and edited manuscript

Certification by Co-Authors

The undersigned hereby certify that:

- the above statement correctly reflects the nature and extent of the PhD candidate's contribution to this work, and the nature of the contribution of each of the co-authors; and
- that the candidate wrote all or the majority of the text.

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CHAPTER 1 INTRODUCTION

Digital technologies are indisputably transforming the global economy and user engagement (IMF 2018), leading to the proliferation and prosperity of digital business. Digital business refers to any business activities that ultimately or auxiliarily proceed with the use of digital technologies and media (Chaffey 2015). One type of digital business is the digital content business. Digital content business refers to the digital business of which goals are realized by engaging customers to consume and interact with content published on digital media (Chaffey 2015). Given that content can be easily exchanged and diffused at an almost zero marginal cost on the Internet (Normann 2001), numerous digital content business models appear (Aral and Dhillon 2021), typically represented by Facebook's advertising (Lee et al. 2018), Youtube and New York Times (NYT)'s premium subscription (Lou and Yuan 2019; Oh et al. 2016), and Second Life's virtual goods franchising (Animesh et al. 2011).

Recently, a new digital content business model, paid question and answer (Q&A), is established on social media for commercializing content created by online influencers (Khansa et al. 2015). Paid Q&A refers to the process of an influential user of a social network (an answerer) answering natural language questions asked by another member of the network (an asker) for a fee (question price). Other users (viewers) in the network can pay a small flat fee to view the answer (viewership). All users can interact with the Q&A via tapping the like, comment, and share buttons (see more details about the operation of paid Q&A in section 1.1.1 Research Context). Uniquely, paid Q&A empowers users to purchase an answer at a nominal price and the asker to share the viewership revenue with the answerer.

Social media platforms, such as Twitter and Facebook, have considerable potential to build a digital business model for content commercialization (TechCrunch 2018). They not only represent an open marketplace where users can produce and consume content but also provide a powerful medium for content propagation and user communication (Leonardi 2014). Online Q&A is an alternative way for users to acquire and share quality and customized answers to personalised questions. Harper et al. (2008) suggest that online Q&A is "*purposefully designed to allow people to ask and respond to questions on a broad range of topics*" (p.866). Although online Q&A sites have been touted as a reliable and valuable portal in which people can seek and search for highly customized and technical advice (Adamic et al. 2008; Shen et al. 2017; Su et al. 2007), they also encounter many challenges, including countless unanswered questions, unsatisfactory question and answer quality, and dwindling user traffic (Moore 2008; Shen et al. 2017). Paid Q&A, an integration of online Q&A, social media, and revenue-sharing mechanism for the host platform, answerer, and asker, becomes a viable digital content business model (Kuang et al. 2019). It enables and incentivizes users to exchange quality content and socialize with other users. This new digital business model has received lots of attention, especially in practice (Fu 2017; Jan et al. 2018b; Technode 2016). However, little academic research has touched this model regarding relevant users' behaviors, e.g., answer consumption and social interactions, in the paid Q&A context.

Based on the unique operation of paid Q&A, this thesis will attempt to explore two types of user engagement behaviors—answer consumption and social engagement—from three perspectives. In particular, it will investigate (1) what drives viewers to pay for a paid answer to the question, (2) what linguistic features of the question content conduce to askers' profit, and (3) how users engage in different social interaction activities which demand distinct cognitive levels. The first two research questions fundamentally focus on the viewers' answer consumption, while the last focuses on users' social engagement.

Prior Q&A literature has made substantial efforts in understanding the answerer and asker's participation motivations (Chen et al. 2019a; Choi et al. 2014; Choi and Shah 2016; Fang and Zhang 2019; Oh and Syn 2015; Sun et al. 2017) and their performance changes when contexts switch from free to paid (Lin 2007; Liu et al. 2021; Zhao et al. 2016; Zhao et al. 2020). Therefore, this thesis, focusing on content consumers (viewers and social interaction users), will supplement the online Q&A literature. More importantly, previous literature mainly focuses on the free context (Qiu and Kumar 2017), while this thesis will theorize user behaviors in the paid context. Therefore, it will contribute to the user engagement and content monetization literature.

In practice, this thesis will help stakeholders (e.g., answerers, askers, and the platform at large) maximize the economic revenue from the paid Q&A business model. This research may realize business goals such as (1) finding out fundamental causes of success or failures, roadblocks, and drawbacks of the prior free and paid Q&A business models (e.g., Yahoo! Answers and Google Answers) and each specific Q&A product, or even foresee and solve potential problems before they occur; (2) understanding answer viewers' consumption experience and interaction with Q&As in the paid Q&A market through the analysis of their behaviors; (3) develop optimum business patterns and make better and more targeted involvement ways in the paid Q&A work for stakeholders to attract more users to ask questions, purchase answers, and enact social interactions; and so forth.

1.1 Research Background

In the digital age, people acquire information and knowledge from two primary sources—search engines and social media. The former performs well in providing rich information and indexing web pages, but it returns more standardized answers and fails to reply to natural-language questions (Morris et al. 2010). The latter enables users to communicate highly tailored questions and generate specialized and customized answers to one single question. Thus social media has huge potential to establish a platform for the question asking and answering.

Compared with search engines, social media is more like a digital space of informal communication (Davison et al. 2018). Many Q&A sites such as Yahoo! Answers, Quora, Zhihu, and Stack-Exchange are preferred sites for users to seek answers or advice related to individual and natural-language questions. Such sites have been rapidly accepted by information seekers, who are overwhelmed by overloaded and paradox information, and by information providers, who are often stuck in selection among substantial questions to answer. The increasing demand from users enlightens social media practitioners to launch paid Q&A business model for improving content quality and social interactions and creating economic and relational benefits. Several leading social media platforms, such as Zhihu and Weibo, have already adopted the paid Q&A model with success (e.g., Ye et al. 2021; Zhao et al. 2020), and more are in the pipeline (e.g., Lopez 2019; Niftycrack.com 2021; Perez 2021).

Social media has the most potential to monetize the Q&A service for two reasons. One is that social media-based Q&A has a huge user base from social media. Global social media statistics show that over 53% of populations are active social media user (Kemp 2021). The vast user base of social media offers an adequate and steady customer base for online influencers to market their content (e.g., answers). The other reason is that social media is a lightweight channel for information spreading and communication (Broersma and Graham 2016). It makes the social media-based Q&A platform easy to use and enables social media users to interact with the paid content. The generated word-of-mouth (WOM) information during social interactions can signal the quality and relevance of the answer to the question (Chevalier and

Mayzlin 2006; Li and Wu 2018; Liu 2006), which will increase the potential of the content monetization (Huang et al. 2019; Lu and Churchill 2014; Morris et al. 2010).

In paid Q&A , such as Fenda, Weibo Q&A, and Zhihu Paid Consultation[1], questions cover a broad variety of topics, including social topics, celebrity gossip, career consultation, financial and investment advice, healthcare, parenting, laws, and so on. As a result, content per se in paid Q&A is not distinct from that on free Q&As. However, the unique social environment and economic incentive may challenge content generation and consumption behaviors and outcomes that were documented in previous Q&A research.

On free Q&A platforms, askers post questions to the *unknown* crowd for answers (Wang et al. 2013). On paid Q&A platforms, askers post questions to specific answerers and pay them for answers (Liu and Jansen 2018). Answers are evaluated by answer viewers' comments, forwards (sharing), and likes (Kanuri et al. 2018). Yahoo! Answer is an example of a free Q&A platform. Examples of paid Q&A platforms include Weibo Q&A (textual answers), Zhihu.com (textual answers) (Zhao et al. 2018), and Fenda.com (audio answers).

Both paid and free share a common trait. Their success is a function of traffic (visitors) or viewership, a proxy of perceived Q&A quality (Ransbotham et al. 2012). The higher the perceived quality, the higher the traffic. However, only a paid Q&A platform can: 1) Motivate askers with explicit economic incentives (profits or losses) to submit questions for which viewers are willing to pay; and 2) motivate askers to contribute questions that are perishable (i.e., their value decays with time). This leads to a constant replenishment of the platform

[1] Fenda.com is a paid Q&A allowing answerers to respond to askers' questions with voice messages, while Weibo Q&A requires answerers to respond with textual messages. Zhihu offers both community-based Q&A service in which users ask and answer questions for free and paid consultation service.

inventory of Q&As and higher traffic. See more details about the two motivations in Section 3.2.1.

1.1.1 Research Context

This thesis will conduct the research based on the context of Weibo Q&A, affiliated to the social media platform, Sina Weibo. Sina Weibo is the largest Chinese social media platform in which rich user-generated content (UGC) generates and diffuses. It was reported that there are over 500 million monthly active users and 224 million daily active users on Sina Weibo (Lin 2021). Weibo Q&A allows users to post, share, and comment on content such as news, original posts, articles, photos, music, videos, and other patterns of content. Social media influencers, such as online celebrities, opinion leaders, and specialists from various industries, build up personal brands on Sina Weibo via publishing original and quality content.

In December 2016, Sina Weibo launched the paid Q&A service, Weibo Q&A, supporting users to exchange content in the form of Q&A (see Weibo Q&A business model in Figure 1.1 and more information in Appendix A) (Fu 2017). Askers create questions, and answerers respond to questions via long texts. Only 500 high-quality users (e.g., opinion leaders and specialists in the platform) were invited first to offer this new service (Zhang 2016). Until the end of July 2017, 36,712 users (i.e., answerers) were successfully authorized with individual landing pages on which other users can ask questions, but only 18,938 of them answered one or more questions. Based on Sina Weibo, Weibo Q&A is not only an online Q&A system but also supports the same social activities with regular social media posts. In this vein, researchers can track user behaviors on Weibo Q&A.

On Weibo Q&A, stakeholders include the host platform, askers, answerers, and answer viewers. Figure 1.1 shows the relationship among all stakeholders. The platform benefits a constant profit portion in all transactions, and *answerers* are those users who register for the Q&A service. They set the price for their answering service and wait for *askers* to pay for proposing a question. Users interested in an answer to a question can pay RMB 1, *the fee of viewership*, to view the answer. They are called *answer viewers*. One viewership is worth RMB 1. The prices set by each answerer vary. Appendix A offers several screenshots to demonstrate the procedure of engaging in Weibo Q&A. Charging for viewership is only valid within three months since the answerer responds to the question. The answerer and asker will equally share the viewership revenue. Weibo takes a 10% commission on all transactions.

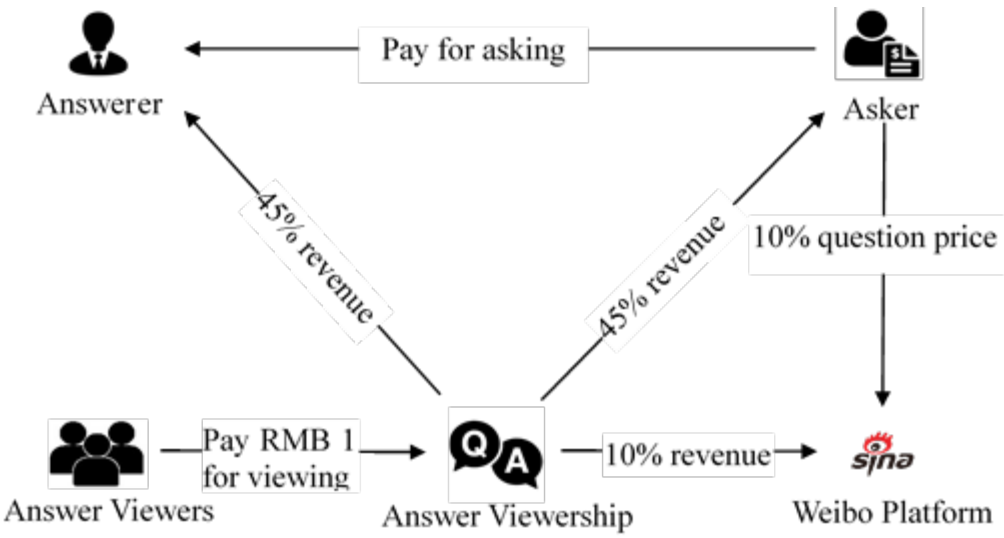

Figure 1.1 Business Model of Weibo Q&A

Figure 1.2 displays the operating procedure of Weibo Q&A. An asker proposes a question to one answerer on a prepayment basis and will obtain a full refund if the nominated answerer does not reply in three days. After the answerer replies to a question, the question with an inserted link to the paid answer will be published on Weibo, waiting for answer viewers to purchase. The asker and answerer will profit from the viewership revenue generated from answer viewers by the same proportion. Although users cannot share the paid answer over their networks directly, they can forward the question with an answer link to their social networks. Users who have observed the question can click the answer link to buy the answer. From this perspective, the paid answer is one type of information goods (Jan et al. 2018b).

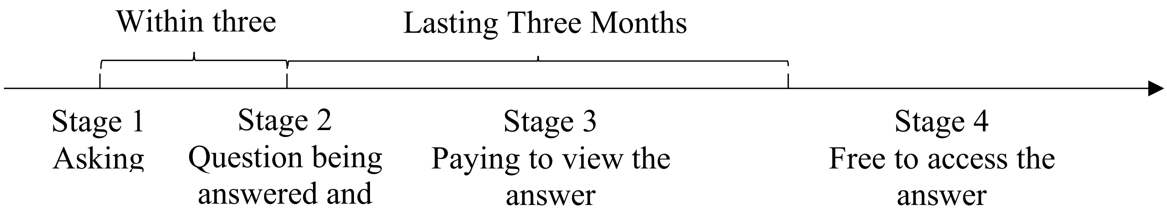

Figure 1.2 The Operational Process of Weibo Q&A

1.1.2 Research Gaps and Motivations

This thesis is motivated to investigate paid Q&A by four research gaps. First, online Q&A is recently established on social media, receiving little academic attention. Online Q&A platforms can be organized into four categories: community-based Q&A (e.g., Yahoo! Answers, Quora, and Stack Overflow), collaborative Q&A (e.g., WikiAnswers), expert-based Q&A (e.g., Dingxiang Doctor and Just Answer), and social media-based Q&A (e.g., Twitter and Facebook) (Choi et al. 2012). This typology is not absolute but identifies their unique characteristics.

In community-based, collaborative, and social media-based Q&As, any users can engage as askers and answerers. While in the expert-based Q&A site, answerers are usually acknowledged experts instead of mass users, and one question can only be answered by one answerer. Although each user can respond to the same question in the first three types of Q&A sites, answerers list their answers separately below one question in the community-based and social media-based Q&As but rephrase the existing response to one question in the collaborative Q&A. Further, as the name indicates, social media-based Q&A site emphasizes social interaction functions. It utilizes the features of social networking sites to facilitate users' knowledge exchange. Recently, social media-based Q&A has grown rapidly and shown breath-taking capacity in attracting users to involve. However, existing research mainly focuses on the other three types of Q&A services (Adamic et al. 2008; Raban 2008; Rafaeli et al. 2007; Regner 2005), especially for the community-based and collaborative Q&A (Bhattacharyya et al. 2020; Chen et al. 2019a; Jin et al. 2016; Liu et al. 2020), limited literature focuses on social media-based Q&A.

Second, prior Q&A literature mainly focuses on the free Q&A. Based on the free context, past studies pay attention to exploring the asker and answerer's participation motivations (Choi et al. 2014; Choi and Shah 2016; Fang and Zhang 2019; Oh and Syn 2015; Sun et al. 2017; Yu et al. 2007; Zhao et al. 2016), the evaluations of the answer quality (Chua and Banerjee 2014; Harper et al. 2008; Jeon et al. 2006; Liu et al. 2020; Zhang et al. 2019b), the conceptualization of online Q&A (Choi et al. 2012; Li et al. 2012; Shachaf 2010), and the interplay between financial incentives and answerers' service efficiency (Hsieh et al. 2010). Recently, a few research investigated the asker's switching from free to paid Q&A services (Jan et al. 2018a; Liu et al. 2021; Zhao et al. 2019; Zhao et al. 2020). However, how to achieve the economic value of the paid Q&A has not received a common concern in the existing literature (Khern-am-nuai et al. 2017). The lack of insights regarding the financial implications of the Q&A system from the literature impedes managers from gaining guidance on deriving relative policies and managerial practices. Specifically, monetization of answer viewership and provision of monetary incentives make theories used in the extant literature less applicable to the context of paid Q&A.

Third, paid Q&A is a new monetization model for social media platforms (Jan et al. 2018b; Zhao et al. 2018). Unlike the freemium model (Aral and Dhillon 2021) and Google Answers[2], paid Q&A charges viewers a nominal flat fee for viewing the answer (Sun 2017), e.g., RMB 1 or US$ 0.145. Monetized content consumption may differ from the consumption of free content (Hoang and Kauffman 2018), which may suffer from the undersupply problem (Goes et al. 2016; Qiu and Kumar 2017). Besides, paid Q&A provides monetary incentives to both askers for proposing questions and answerers for answering questions (see more details in Section 3.2.1). It allows all stakeholders (askers, answerers, and the host platform) to share the paid viewership revenue (Jan et al. 2018b; Zhang 2016). The provision of monetary incentives may change the nature of user engagement (Oestreicher-Singer and Zalmanson 2013). This revenue sharing mechanism incentivizes both askers and answerers to contribute greater quantity and quality content (Hsieh et al. 2010; Tang et al. 2012), which in turn attracts more engagement of viewers (Kuang et al. 2019) and social interactions (Bapna et al. 2018). In this way, this business model helps arguably avoid the dwindling user traffic and unsatisfactory content sales that were attributed to the failure of past paid Q&As (e.g., Google Answers) (Bogatin 2006; Helft 2006) and free Q&As (e.g., Yahoo! Answers) (Statt and Peters 2021). Thus, it is critical to have a comprehensive investigation on the user behaviors in such an unique context.

Fourth, Q&A has barely been discussed in the context of China, while Weibo is one of the largest Chinese social media. Most researchers concern them more in the USA (e.g., Bouguessa et al. 2008; Li et al. 2012; Shen and Wang 2017), and a few in Korea (Jeon et al. 2006). Chinese net-users share different social behaviors and consumption opinions with users in other

[2] Google Answers was an online Q&A system that was launched by Google in 2002 and shut down in 2006. The process of Google Answers is that users offer a price and propose a question, and then answerers choose available questions to respond.

countries due to culture and lifestyle differences. Cross-cultural literature indicates that an individual's social activity and economic performance are greatly influenced by culture (Zheng et al. 2014). The fast-developing information economy and enormous netizens in China also urge us to focus much more on Chinese Q&A. Thus, exploring Chinese platforms will add to Q&A research.

Thus, it is crucial, from the perspective of economic benefit, to investigate the underlying mechanisms of stakeholders. This study attempts to bridge this gap through three empirical studies on Weibo Q&A.

1.2 Research Focus and Questions

The research objectives of this thesis are to understand what drives *answer viewers* to pay for paid answers, how *askers* frame a profitable question content, and whether *users* engage in social interaction activities, i.e., likes and comments, differently.

Business activities associated with the paid Q&A take place in two stages and include three types of user engagement. At the first stage, the business occurs between the asker and the answerer. In this stage, askers engage in the paid Q&A via paying to an answerer for seeking an answer. After the answerer responds to the question, the settled question will be published to the answerer's social network automatically and appears in his/her followers' Home timelines, which leads to the next stage. At the second stage, the business occurs between the answer viewers and the answerer. Users interested in the answer to the question can pay the viewership fee to view the answer. In this stage, all users can engage in the paid Q&A post via interacting with the content, e.g., liking, comment on, and sharing the paid Q&A.

Prior research has made a substantial effort in exploring answerers' social and financial motivations to contribute answers (e.g., Chen et al. 2019a; Huang et al. 2018; Jin et al. 2015; Phang et al. 2009; Qiu and Kumar 2017) and factors that impact askers to propose questions (Choi and Shah 2017; Liu et al. 2021; Zhao et al. 2019; Zhao et al. 2020). This thesis will focus on other relevant users (e.g., answer viewers and social interaction users) and other distinct engagement activities (e.g., answer viewers' paying for answers, askers' question framing, and users' social interactions with the paid Q&A). Therefore, this thesis will have a comprehensive understanding of the novel paid Q&A business model from the three angles. Precisely, this thesis consists of three essays as listed in the following sections.

(1) Study 1: Signaling Interactions for Content Commercialization: Exploring the Viewership of Paid Q&A

As a novel business model, paid Q&A on social media platforms enables users (answerers) to charge others (askers) a price for answering personalized questions. Other users (viewers) must pay a smaller fee to view the answers. The provision of monetary incentives and fee-based answer viewership challenge our understanding of content consumption. Given that extant literature has mainly studied free content consumption, little is known about what contributes to the monetized answer viewership. Drawing upon the signaling theory, this study strives to fill this gap by developing a model on monetized content consumption. It theorizes the impacts of various cues on answer viewership, including intrinsic signals (i.e., answer's social favor, diffusion, and feedback that one answer received) and extrinsic signals (i.e., answerer's social media status and popularity, and the question price). It also hypothesizes differential moderating effects of the question price (monetary incentives for Q&A). By analyzing unique panel data from Weibo Q&A, this study finds that answerers' social media status and popularity and answer's social favor, positively affect answer viewership. Interestingly, this study finds that question price positively moderates the impacts of social media status, social favor, and social diffusion but negatively moderates those of social media popularity and social feedback. The study highlights some unintended and heretofore undocumented effects and enriches our understanding. It also sheds light on how the new content monetization strategy operates and how other similar platforms (e.g., crowdsourcing and UGC) may profit from this strategy.

(2) Study 2: Toward Profitable Questions in Paid Q&A: A Perspective From Question Framing

Despite the success of the paywall model for digital news and music, many content platforms are still struggling to transform their operations for survival in the digital era (Bharadwaj et al. 2013). Recently, the profit-share scheme creates a new opportunity for paid Q&A to retain users. It allows askers to share the answer viewership revenue with answerers, which advantages to fulfill askers' extrinsic needs, such as offsetting question cost and gaining a profit. This study explores how askers can maximize their profits by framing a popular question. Drawing upon social presence theory, this research identifies two content features—question informativeness and sentiment extremity—exemplifying the social presence of the question content. This study tests a polynomial regression model with 9,223 unique fee-charged questions from Weibo Q&A. The construct operationalization is based on the collected textual data (i.e., question content) and implemented with the text analysis tool, i.e., LIWC. Results show that question informativeness has an inverted U-shaped relationship with askers' financial gain, and sentiment extremity has a positive relationship. The findings contribute to the previous literature by proposing a nuanced research model that demonstrates the impacts of question content features on askers' financial gain from paid Q&A. Also, question askers, answerers, and the host platform can acquire practical implications from our findings.

(3) Study 3: Understanding Different Cognitive Levels of Social Engagement: Evidence from Paid Q&A

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 the like volume and comment volume to measure social engagement without considering their differences. This study conceptualizes that *liking* and *commenting* on content are two distinct behavioral manifestations with different cognitive processes involved: low- and high-cognitive social engagement. Specifically, setting in a paid Q&A site, this research identifies the answerer characteristics (i.e., social media popularity measured by follower volume and voluntary contributions measured by free post volume) and the answer characteristic (i.e., viewership revenue) as salient factors influencing social engagement. This study compares their direct and interaction effects on the two types of social engagement. Results show that identified factors have a greater direct effect and a smaller interaction effect on low-cognitive social engagement (i.e., *liking*) than on high-cognitive social engagement (i.e., *commenting*). The work advances knowledge of social engagement and has practical implications for platform practitioners to achieve social engagement.

1.3 Expected Contributions

This thesis is expected to contribute to the literature of Q&A, paid content consumption, and user engagement with three empirical studies based on the paid Q&A context. Fundamentally, this thesis will contribute to the literature on online knowledge exchange and collaboration communities (Bhattacharyya et al. 2020; Liu et al. 2020) as well as the burgeoning literature on paywalls (Aral and Dhillon 2021; Oh et al. 2016; Pattabhiramaiah et al. 2019; Zhang et al. 2020).

On the one hand, prior research on online knowledge communities has theorized various engagement behaviors, including free of charge knowledge seeking (Pan et al. 2017), voluntary and virtual-rewarded knowledge sharing (Huang et al. 2018; Khansa et al. 2015; Zhao et al. 2016), and social engagements in the free context (Yang et al. 2019). However, there is a lack of knowledge about user engagement in the paid content environment. Paid Q&A represents a new digital business model of knowledge exchange and content collaboration, which charges users to ask questions and/or view answers. This thesis will distinguish paid Q&A users' answer consumption and social interaction behaviors from previously documented user engagement at a finer granularity through identifing quantitative and qualitative antecedents of the answer consumption and social interactions.

On the other hand, prior digital paywall literature has identified and examined antecedents and outcomes of a paywall in various industries, including news (Lambrecht and Misra 2017; Oh et al. 2016), music (Bapna et al. 2018; Bapna and Umyarov 2015; Dewan and Ramaprasad 2014), video-on-demand (Matos and Ferreira 2020), and games (Animesh et al. 2011; Mäntymäki and Salo 2015). This thesis focuses on the Q&A domain, a new emerging and popular business model that monetizes online content. It thus represents a much-needed enrichment of the literature on digital paywalls.

This thesis will add to the information systems (IS) literature in more specific ways via the three studies. First, this thesis will extend content consumption literature by theorizing Q&A relevant characteristics as content quality signals. This thesis can provide insights into what factors drive users to pay for online content and how identified factors interactively impact users' decisions by adopting signaling theory and previous research. This research will strengthen prior literature on how online users attend to and interpret pertinent cues relating to the product. Significantly, based on the paid Q&A context, this work aims to address the knowledge gap of how paid Q&A stakeholders (e.g., answerers and the host platform) can increase the attractiveness of the paid content.

Second, building on social presence theory and relevant literature, this thesis will identify the linguistic features included in the question content and examine their impacts on answer consumption, and hence askers' profits from the paid Q&A. This thesis will contribute to the literature on consumer experience in online paid content consumption. Results will help understand how some linguistic features of the content influence content consumers' preference to and perceived value of the content. They will also address the knowledge gap of why online content reflecting certain linguistic styles can be commercialized directly.

Third, this thesis may pave the way for future nuanced investigations on social engagement. Prior studies have examined many antecedents and outcomes of social engagement activities in UGC communities. Yet, limited research differentiates various types of social engagement that are measured by the number of likes, shares, and comments that content receives.

Psychology literature has found that different types of social interactions are the results of different cognitive pathways. By adopting dual-process theory and uses and gratification theory, this thesis should add to the social engagement literature by identifying antecedents of social engagement in the paid Q&A context and examining their differential impacts on different behavioral manifestations.

Apart from research contributions, this thesis should also contribute to practice. It will provide the platform practitioners and content creators with insights into how to attract and motivate users to purchase and interact with paid content. First, the identified quantitative and qualitative variables investigated in this thesis can help social media and Q&A platforms better manage content creators' awards system (e.g., membership level, social media popularity, answering fee, and viewership fee), design user-interaction functionalities (e.g., following, liking, commenting, and sharing), and guide content creators (e.g., askers and answerers) to produce favorable content.

Further, social interaction performance (e.g., like and comment volume) is a critical impact on users' perceived quality of the content and their content consumption. Thus, this thesis will further explore what and how factors influence users to engage in distinct forms of social engagement in the paid context. Results should offer suggestions for content creators to manage their activities in the platform. For example, answerers usually attract followers via publishing posts on social media. However, overloaded posts may decrease users' chance to observe paid content. Overall, this thesis offers practical suggestions for the platform, answerers, and askers to maximize their economic benefits from paid Q&A and provides practical implications to other similar digital content business models.

1.4 Thesis Organization

Chapter 1 has offered an outline of the thesis by introducing the research background and setting, the primary motivations based on the current research gaps, the objectives this thesis aims to meet, and the expected contributions this thesis will make. Subsequent chapters are organized as follows.

Chapter 2 reviews the prior relevant literature. It first offers an overview of the previous literature of online Q&A. Then, it provides an overview of the previous literature on the digital business model. In the two sections of the literature review, detailed analyses of how prior research helps implement each study are offered. Lastly, it theorizes the context of paid Q&A.

Chapter 3 depicts study 1 in detail. It first reviews prior Q&A literature, identifies research gaps, introduces signaling theory, and explains the dual role of question price. Then, it develops hypotheses for explaining the direct and interaction effects of social signals (e.g., an answerer's membership level and social media popularity, and an answer's like, forward, and comment volumes), and question price on the answer consumption. Fixed effects panel model and instrumental analysis are employed to test the proposed hypotheses. Discussions of the implications, limitations, and future research are given subsequently.

Chapter 4 depicts study 2 in detail. It first reviews prior research examing the impacts of linguistic features on user behavior and explains the social presence theory that can theorize the constructs in the study. Based on the theoretical background, this study identifies two constructs—question informativeness and sentiment extremity—that would impact askers' profit from the paid question. It then develops the research model and hypotheses based on the social presence theory and relevant research. A polynomial regression model helps test all hypotheses in the model. The implications and future research of this research are then discussed subsequently.

Chapter 5 depicts study 3 in detail. It reviews prior literature on social engagement, identifies relevant factors, introduces the dual-process theory and the uses and gratification theory, and develops the hypotheses on users' social engagement in the paid Q&A context. Random effects panel model and robust cluster regressions are employed to examine the research model and proposed hypotheses. Discussions of the implications and limitations of this research are then reported.

Chapter 6 concludes the findings and implications of each study in this thesis. It also offers limitations and the directions of future research on paid Q&A

CHAPTER 2 THEORETICAL BACKGROUND

This chapter first reviews the literature on online Q&A and digital paywall. When discussing each literature stream, there will be an analysis of how prior literature conduces to the conduct of current studies in this thesis. It then theorizes the contextual features of paid Q&A.

2.1 Literature Review of Online Q&A

Although the number of Q&A studies is relatively small due to a short history and tortuous evolution (e.g., the demise of Google Answers), a variety of topics have already been discussed in the previous literature. Existing research on online Q&A has focused on three major aspects. They are platform-centered research, content-centered (questions and answers) research, and user-centered research, respectively.

Platform-centered research has mainly focused on the Q&A collaborative norms (Butler et al. 2002; Li et al. 2012; Shachaf 2010), typology of Q&A systems (Choi et al. 2012; Srba and Bielikova 2016), and distribution characteristics and patterns of answerers, askers, and other users' activity lifespans in various Q&A sites (Adamic et al. 2008; Nichols and Kang 2012; Shen and Wang 2017; Yang et al. 2010; Zhang et al. 2007b). Although each community member can create and evaluate knowledge (Gazan 2006), there is a heavy tail in both the asker and answerer's activities. Top answerers in the community-based Q&A platforms (e.g., Yahoo Answers) account for a small percentage of answerers but contribute most answers (Li et al. 2012; Nam et al. 2009; Shen and Wang 2017). An overwhelming majority of askers post only a couple of questions (Nam et al. 2009). Nichols and Kang (2012) found that 42% of users would provide answers to strangers' questions, and 44% of answers were offered within half an hour on the Twitter-based Q&A platform. Users have more interest in factual questions associated with expertise sharing, social relationship discussion, life and work advice (Adamic et al. 2008), and entertainment-oriented questions (Shen and Wang 2017). Therefore, more users gather to engage in those types of questions as askers and/or answerers.

Content-centered research has mainly investigated practical methods identifying answer quality and satisfaction (e.g., Agichtein et al. 2008; Liu et al. 2008) and factors influencing the answer quality, answer quantity, and response speed (Chua and Banerjee 2013; Harper et al. 2008; Hsieh et al. 2010; Savolainen 2012; Shen and Wang 2017; Teevan et al. 2011). Specifically, Q&A literature suggests that there are several quantitative and qualitative factors. Quantitative factors include the question topic (Harper et al. 2008), question type (e.g., factual questions or nonfactual questions) (Harper et al. 2008; Shen and Wang 2017), and monetary rewards (Harper et al. 2008). And qualitative factors include the question length (Shen and Wang 2017) and the rhetorical features of the question (e.g., ending with a question mark, being succinct, specifying the audience, etc.) (Harper et al. 2008; Teevan et al. 2011).

The detailed information about the content-centered studies is shown in Table 2.1. This literature stream offers insights that the quantitative variables measured by answerer, asker, and the content's characteristics and the qualitative variables identified from the question content can influence the answer quality and adoption. Hence, the literature review also indicates that those variables may impact viewers' answer consumption in the paid Q&A context where viewers cannot evaluate the answer before payments but can refer to other relevant cues. Those findings will inform the conduct of study 1 in chapter 3 and study 2 in chapter 4 which are associated with the answer consumption. The relevant chapters will provide specific elaborations on that later.

Table 2.1 Content-centered Research of Online Q&A

Study	Methods	Key Findings
Agichtein et al. (2008)	Secondary data of 6,665 questions and 8,366 question-answer pairs **Perspective of Analysis:** answers	The established graph-based model can identify high-quality answers from other answers with an accuracy close to the human selection.
Liu et al. (2008)	Secondary data from collaborative Q&A sites and experimental data that people report and rate based on several thousands of questions **Perspective of Analysis:** askers	Askers have greater satisfaction with answers to subjective questions, and their previous asking experience helps predict their satisfaction with the answer; Notably, the answerer's reputation does not increase askers' satisfaction.
Harper et al. (2008)	Secondary data of 3,000 questions with 5,356 answers from six community Q&A sites **Perspective of Analysis:** answers	Answer quality is higher in a fee-based site than in the free sites, and paying more can lead to better answers.
Hsieh et al. (2010)	Secondary data of 800 questions from a paid Q&A site **Perspectives of Analysis:** askers and answers	Paying more leads to more and longer answers but may not lead to higher quality answers.
Teevan et al. (2011)	Secondary data of 282 users' questions in Facebook **Perspective of Analysis:** questions	Questions that are ended with a question mark, specifying the target audience, and are succinct can increase the answer speed, answer quantity, answer quality.
Savolainen (2012)	Secondary data of 100 threads on discussing global warming in Yahoo! Answers **Perspective of Analysis:** answers	Answers including more oppositional and mixed arguments make users perceive higher answer quality and credibility.
Chua and Banerjee (2013)	Experiment data of 106 questions with a total of 276 answers. **Perspective of Analysis:** answers	The relationship between answer quality and answer speed is insignificant across all questions but significant across question types.
Shen and Wang (2017)	Secondary data of top answerers and their associated askers in Yahoo! Answers **Perspectives of Analysis:** askers and answers	Factual questions receive a fewer number of answers.

User-centered research has mainly studied user involvement predictors and motivations. It has been found that website artifacts (e.g., incentives), users' personal features (e.g., gender and race) (Hannák et al. 2017), membership level, and past behaviors drive users to participate in Q&A service (Khansa et al. 2015). Specifically, research indicates that an answerer's motives are manifold. They have intrinsic motivations (e.g., altruism, self-learning, self-presentation, self-enhancement, and moral obligation) (Guan et al. 2018; Lou et al. 2013; Nam et al. 2009; Yu et al. 2007), social motivations (e.g., followers, followees, and votes volume) (Constant et al. 1996; Guan et al. 2018; Lou et al. 2013; Shen and Wang 2017), and monetary rewards motivations (Chen et al. 2010; Jan et al. 2018a; Lee et al. 2013). More importantly, literature also finds that monetary rewards can mitigate the influence of answerers' intrinsic motivations (James Jr. 2005; Kruglanski et al. 1975; Zhao et al. 2016). As for research on askers, they tend to stay in the community longer if they receive quality answers (Yang and Wei 2009). Answers with high quality, provided by credible answerers, and affording emotional support (e.g., fulfilling cognitive needs and acquiring fun) can increase askers' answer adoption likelihood (Choi et al. 2014; Jin et al. 2016; Zhao et al. 2018). Recent studies also investigate several factors that might influence their payment intentions and decisions (Choi and Shah 2016; Liu et al. 2021; Zhao et al. 2020).

Table 2.2 offers a clear review of relevant empirical studies of the answerer and asker's motivations. This literature stream suggests that (1) prior literature has investigated a lot on answerers' knowledge contribution behavior in online Q&A, hence there is a need to study other user behaviors, and (2) the question price might have more nuanced impacts on the answer quality, which might influence the answer consumption contingently. They will inform the conduct of study 1 in chapter 3, in which more comprehensive explanations will be offered.

Table 2.2. Empirical User-centered Research of Online Q&A

Focus	Study	Methods	Key Findings
Answerer	Nam et al. (2009)	Secondary data of 2.6 million Q&As posted between 2002 and 2007	Altruism, learning, and capacity are typical motivations for answerers to share knowledge; Users participating more frequently perform better in knowledge quality.
	Yang and Wei (2009)	Secondary data of 2.7 million users from a community-based Q&A site	Answerers who contribute more content will receive more rewards; The sense of community increases users to engage more.
	Chen et al. (2010)	A field experiment at Google Answers	The question price is positively related to longer but not better answer; Answerers with higher reputations contribute better answers.
	Lee et al. (2013)	A survey study of 245 answerers from Jisiklog.	Answerers are motivated to participate in Q&A service by financial incentives and intrinsic motives instead of social factors.
	Lou et al. (2013)	An online survey of 367 participants from a community-based Q&A site	Extrinsic rewards (e.g., reputation), learning, self-efficacy, and enjoy helping are important participation motivations; Extrinsic rewards are more effective in increasing answer quantity than quality, while self-efficacy is more effective in answer quality.
	Khansa et al. (2015)	Panel data of 2920 users on Yahoo! Answer	Artifacts (e.g., incentives), membership (e.g., level and tenure), and habit (e.g., past behavior) drive users to participate in the Q&A service.
	Zhao et al. (2016)	Secondary data collected from a community-based Q&A	Virtual organizational rewards can reduce the effect of enjoyment in helping on the attitude to knowledge sharing; Reciprocity can undermine the impact of self-efficacy; The moderation effect of virtual organizational rewards on enjoyment in helping depends on users' activity level.
	Guan et al. (2018)	Secondary data of users in a community-based Q&A	The identity-based trust, previous feedback, social exposure likelihood, WOM, and reciprocity pressure can increase continued contribution.
	Shen and Wang (2017)	Secondary data from Yahoo! Answers	Users ask more questions than answering others' questions; Users participate in knowledge categories that they seldom indicate in the profile.
	Jan et al. (2018b)	Case study of two paid Q&A (China's Fenda and US's Whale)	Payments motivate answerers to respond more quickly; Proactively adjust the answering price is profitable.

Asker	Constant et al. (1996)	Survey of employees from a global computer manufacturer	Askers rate answers that are replied out of organizational motivation more useful.
	Hsieh et al. (2010)	Secondary data of 800 questions from a paid Q&A	Askers tend to pay when asking factual questions and are willing to pay more when their questions are more difficult.
	Choi et al. (2013)	Secondary data of 500 questions from Yahoo! Answers, WikiAnswers, the Internet Public Library, and Twitter	Users are primarily motivated to ask a question by fulfilling cognitive needs and acquiring fun from high-level category tension-free needs.
	Choi and Shah (2016)	Online survey on Yahoo! Answers, and WikiAnswers	Cognitive needs are the most significant motivation to facilitate question asking; Other motivations (e.g., tension-free satisfaction) also positively impact asking. But, their effects depend on askers' situations.
	Jin et al. (2016)	Secondary data collected from Baidu Knows	The answer quality, emotional support, and answerer credibility can positively influence the answer adoption likelihood; The competition among answerers and the involvement of recipients positively moderate the above relationships.
	Hannák et al. (2017)	Secondary data of 13,500 users in online Q&A	Askers' gender and race significantly impact the evaluations of answers.
	Zhao et al. (2018)	Panel data of 2340 answerers from Zhihu.com	Answerers' reputation, ability, and integrity motivate users to pay for asking; Price positively moderates the relationship between asker's trust and payment decision.
	Zhao et al. (2018)	Secondary data from Zhihu.com	Answerers' reputation, ability, and integrity enhance askers' payment decisions; Question price enhances the impact of answerers' trust on askers' payment decisions.
	Zhao et al. (2020)	An online survey of 322 askers from Fenda	Non-monetary factors (e.g., self-enhancement, social support, and entertainment) and monetary factors (e.g., cost and benefit) impact engagement. And, perceived reciprocity moderates the effect of financial benefits.
	Liu et al. (2021)	Interview data of 64 askers from a community-based Q&A	Askers' intention to switch from free to paid Q&A can be impacted by their dissatisfaction with the free Q&A, satisfaction with the paid Q&A, and other social, personal, and situational factors.

2.2 Literature Review of Digital Business Model

Digital technologies, such as digital content-streaming systems, have spawned out mass content (Dixon 2013). Given that the content can be exchanged at low transaction costs and shared at almost zero marginal cost (Hansen Henten and Maria Windekilde 2016), digital content providers prefer to market and sell digital products to content consumers directly (Hoang and Kauffman 2018). As a result, numerous digital business models emerge, such as NYT's paywall (Oh et al. March 2016), Second Life's virtual goods franchise (Animesh et al. 2011), Youtube's advertising revenue (Kim 2012), etc.

Platforms have three ways for monetizing digital products online (Lambrecht et al. 2014). First, it can monetize the content or service that is available for users on the platform directly, such as NYT and Paid Q&A. Second, the platform can price the data about users, such as cookies. Third, it can receive revenue from advertising, such as Youtube and Facebook. One platform may choose one of the three business models or adopt a hybrid business model consisting of two or three business models.

Further, platforms launch three types of content monetization models, i.e., ad-sponsored model, premium subscription model, and pay-per-item model. Ad-sponsored model refers to that the platform makes profits by selling advertisement reservations, such as such as YouTube and Hulu (Sun and Zhu 2013). Premium subscription model requires users to make monthly or yearly payment to access content, such as NYT and Last.fm (Bapna et al. 2018; Oh et al. 2016). Pay-per-item model charges users for each piece of content, such as Paid Q&A.

Existing literature on the digital business model can be organized into two streams: antecedents and outcomes of adopting the digital business model. Table 2.3 summarizes prior empirical studies on the antecedents of the digital business model. Research has identified several factors impacting the revenue of the digital business model, including social engagement (Dewan and Ramaprasad 2014; Oestreicher-Singer and Zalmanson 2013), peer influence (Bapna and Umyarov 2015), free content provision (Lambrecht and Misra 2017), periods of adopting the digital business model (Lambrecht and Misra 2017), user characteristics (heavy or light users) (Godinho de Matos and Ferreira 2020; Lambrecht et al. 2014), content quality (Fan et al. 2007), content type (e.g., trendiness, entertainment) (Dou et al. 2017; Mäntymäki et al. 2020), price promotions, and reference effect (Pauwels and Weiss 2008; Xu and Duan 2018). Moreover, it has also been found that the content provider should adjust the proportion of allocating premium subscription, free content, and advertising space for optimizing the total revenue (Dou et al. 2017; Pauwels and Weiss 2008; Xu and Duan 2018). This literature stream will guide this thesis to develop study 1 which explores the antecedents of the sales of paid content.

Table 2.3 Empirical Studies Related to Antecedents of Digital Business Model

Revenue Model	**Study**	**Constructs and Method**	**Key Findings**
Ad-sponsored model	Fan et al. (2007)	Independent Variables: • Content quality • Advertising revenue • Ease of use of the paywall Dependent variables: • Pricing • Advertising level **Method:** Decision model	The content provider should adopt the pricing strategy for high-quality content and when the online access cost is low; When the online access cost is high, the content provider should adopt the advertising strategy; The optimal strategy is that the content provider adopts both pricing and advertising strategies.
	Xu and Duan (2018)	Independent Variables: • Reference effect Dependent variable: • Pricing and advertising **Method:** Game-theoretic model	The content provider should adopt the pricing strategy when users have less sensitivity to the advertising; When users focus more on experiences, the provider

			should adopt the advertising strategy; When the content provider pays less attention to the reference effect, s/he will overestimate the pricing strategy's profit.
Premium subscription model	Pauwels and Weiss (2008)	Independent Variables: • Search engine referrals • Targeted e-mail offers • Price promotions • Free-to-fee conversion e-mail Dependent variables: • New free subscriptions • New monthly subscriptions • New yearly subscriptions • Monthly subscription price • Yearly subscription price **Method:** Natural experiment with the panel data collected from an online content provider	Price promotions are positive in attracting new monthly subscriptions, and e-mail and search-engine referrals are significantly positive in attracting yearly subscriptions; Although free-to-fee conversion e-mail blasts can increase subscription revenue, they also reduce advertising revenue; The buildup of impetus in new free subscriptions can conduce to the success of free-to-fee subscriptions.
	Oestreicher-Singer and Zalmanson (2013)	Independent Variables: • Users' content consumption • Content organization, e.g., creating playlists and tags • Community participation • Community leadership Dependent variable: • Payment: nonpaying user or subscriber **Method:** A random sample of 39,397 nonpaying users and 3,612 subscribers in Last.fm	When users climb the "ladder of participation" (the lowest ladder is simply consumption, then content organization, community participation, and the highest is leadership), their payment willingness increases; Community participation has a more significantly positive influence on willingness to pay than content consumption.
	Bapna and Umyarov (2015)	Independent Variables: • Peer influence • Number of friends • product adoption Dependent variable: • Odds of purchase **Method:** Panel data of 3.8 million users from Last.fm	Peer influence has a significant effect on product adoption; Users with a small number of friends have a higher adoption likelihood.

	Mäntymäki et al. (2020)	Independent Variables: • Enjoyment • Price value • Intrusiveness of advertising • Ubiquity • Social connectivity • Discovery of new content Dependent variable: • Intention to upgrade/retain the premium subscription **Method:** Survey data of 467 responses from Finnish Spotify users	Enjoyment and price value of the paid subscription increases users' intention to upgrade; Ubiquity and the discovery of new content increase users' intention to retain the premium subscription; Social connectivity hurts the intention to retain the premium subscription; The intrusiveness of advertising in the free subscription has a negative effect on the paid subscription's price value.
	Godinho de Matos and Ferreira (2020)	Treatment: • Binge-watching Dependent variable: • Premium subscription **Method:** A natural experiment of 30,000 households	Binge-watching decreases the household's interest in the content and reduces their willingness to pay in the short term.
Pay-per-item model	Lambrecht et al. (2014)	Independent Variables: • Consumer type: high and low demand consumers • Time: off-season and on season Dependent variable: • Unique visitors **Method:** Panel data of paid and free articles about six types of sports in ESPN.com	The platform should provide paid content during the off-season (i.e., when people has low demand of content) and free content during the in-season (i.e., when people has high demand of content); Low-demand consumers are more sensitive to paid content than high-demand consumers.
	Dewan and Ramaprasad (2014)	Independent Variables: • New Media: blog buzz • Traditional Media: radio play • Music type Dependent variable: • music sales at album and song levels **Method:** Panel data of 1000 songs and 594 albums across 24 weeks from Nielsen SoundScan and relevant blog buzz from Google Blog	Traditional media positively influences both song and album sales; Social media buzz only negatively influence song sales; The negative effect of social media buzz is more significant for niche music than mainstream music.

	Dou et al. (2017)	Independent Variables: • The depreciation of consumer's vintage valuation • The depreciation of consumer's individual valuation • Network effects Dependent variable: • Pricing and leasing strategies **Method:** Game-theoretic model	For vintage depreciation content, the vendor should mainly adopt a leasing strategy to make a profit; For individual depreciation content, the vendor should adopt the selling strategy when the extent of individual depreciation exceeds a threshold, otherwise leasing strategy; Network effects negatively moderate the impact of vintage depreciation on vendor profit; The moderation effect of network effects can be either positive or negative, depending on the extent of individual depreciation.

Table 2.4 summarizes the second literature stream, which investigates the outcome of adopting the digital business model. Research has found that the introduction of digital business model, e.g., premium subscription, influence the generation of WOM (Oh et al. 2016), platform traffic (Chiou and Tucker 2013), users' social engagement (Bapna et al. 2018), and content engagement (Aral and Dhillon 2021; Bapna et al. 2018; Chiou and Tucker 2013). The monetization of content also moderates the impact of WOM and peer effect on content consumption (Bapna et al. 2018; Oh et al. 2016). The decrease in content and social engagement will damage the advertising revenue (Aral and Dhillon 2021). Thus, it is also critical to retain users' social engagement activities in the paid platform. This literature stream guides the conduct of study 3 in chapter 5 which discusses the distinct cognitive pathways to different social engagement activities.

Table 2.4 Empirical Studies Related to Outcomes of Digital Paywall

Study	Constructs	Methods	Key Findings
Chiou and Tucker (2013)	Independent Variable: • The implementation of a digital paywall Dependent variables: • Website traffic	Natural experiment with the panel data from Experian Hitwise and Compete **Unit of Analysis:** Visit level	The introduction of a paywall leads to a 51% drop in visits.
Oh et al. (2016)	Independent Variable: • The implementation of a digital paywall Dependent variables: • The pattern of online WOM • The effectiveness of online WOM	A natural experiment with the panel data from social media and NYT **Unit of Analysis:** Article level	Implementing a digital paywall exerts a long-tail effect on the distribution of WOM that is related to popular and niche articles; Implementing a digital paywall can weaken the influence of WOM on website traffic.
Bapna et al. (2018)	Independent Variable: • The decision to pay for a premium subscription Dependent variables • Content-related social engagement, e.g., listen to songs • Community-related social engagement, e.g., create playlists • Peer influence, e.g., gain friends	Panel data of 3.9 million users from Last.fm **Unit of Analysis:** User level	Paying for premium has positive effects on both content-related and community-related social engagement and peer effect.
Aral and Dhillon (2021)	Independent Variable: • The implementation of a digital paywall Dependent variables: • Content demand: number of articles read by users • Subscriptions	Natural experiment with the panel data of 29 million users from NYT **Unit of Analysis:** User level	The policy of digital paywall reduces content demand by around 9.9%, which decreases the advertising revenue; The paywall policy leads to a 31% growth in the total subscriptions (free and fee), which increases the total platform revenue.

2.3 Theorization of Paid Q&A

Paid Q&A platforms differ from conventional Q&A ones in that both answerers and askers receive considerable economic incentives from contributing Q&As, and the generated answers can be purchased by other users, i.e., answer viewers. The product, paid answer, in the paid Q&A platform has four unique characteristics. First, it is one type of experience goods. Unlike free content such as free Q&A, viewers cannot evaluate the quality of the answer before making payments (Bourreau and Curien 2007). Second, the paid answer is rival goods. Viewers' consumption of one piece of free content does not decrease their availability to others (Lambrecht et al. 2014). In contrast, since paid answers require viewers to pay for it, people would select the preferable ones among many options. Due to the two unique characteristics, online users require relevant cues to help them evaluate the quality and make decisions.

Third, there is a financial cost of generating a paid answer on paid Q&A, namely question price. Besides the flat fee of viewing an answer, the question price might also impact a viewer's attention and expectation to the paid answer. Research has suggested that financial factors have a complicated influence on various users but are highly underestimated in the prior studies (Kuang et al. 2019; Zhao et al. 2016).

Fourth, similar to the common social media content, topics of paid Q&As on social media-based Q&A are also trendy and socially perishable. It means that the popularity of one paid Q&A tends to have a very short shelflife. The social perishability feature stimulates a constant replenishment of Q&A inventory and helps achieve higher platform traffic. These unique contextual features challenge our current understanding of content consumption that is primarily related to free content (e.g., Dewan et al. 2017; Ransbotham et al. 2012).

Although extant literature has provided valuable insights on the engagement and consumption of free content, these insights may not readily explain the fee-charging content. Therefore, this thesis will conduct three separate empirical studies exploring content consumption and social interaction activities based on the unique features of paid Q&A.

CHAPTER 3 STUDY 1: SIGNALING INTERACTIONS FOR CONTENT COMMERCIALIZATION: EXPLORING THE VIEWERSHIP OF PAID Q&A

3.1 Introduction

In the past decade, we have witnessed a growing popularity of digital content. In 2021, the global market of digital content generated USD 293 billion in revenues and was expected to reach 414 billion in 2025 (JuniperResearch 2017; Statista 2021). Digitization of content has enabled numerous new business models and monetization opportunities (Bharadwaj et al. 2013), e.g., subscription or pay-per-item. The subscription revenue model, in which users make periodic payments to access digital content, includes New York Times (NYT)' paywall (Oh et al. 2016), Sina Weibo content subscription (Sun and Zhu 2013), and group subscription service in Facebook (Constine 2018). The pay-per-item revenue model, in which users pay for each digital item, includes paying for virtualized products (Animesh et al. 2011; Kim et al. 2018) and textual, audio, or video content (e.g., iTunes or YouTube movies) (Hoang and Kauffman 2018).

The recent introduction of paid Q&A based on social media platforms (named paid Q&A later) represents a new pay-per-item revenue model for digital content (Jan et al. 2018a; Technode 2017). Paid Q&A refers to the process of a member of a social network (an answerer) answering natural language questions asked by another member of the network (an asker) for a fee. Community-based Q&A refers to the process of inviting the unknown crowd to answer the personalized question. Like community-based Q&A platforms, e.g., Yahoo! Answers, Quora, and Google Answers, social Q&A platforms can generate personalized and interactive answers (Liu and Jansen 2018).

As an important research area for both researchers and practitioners, extant literature has mainly studied the consumption of *free* content (Datta et al. 2018; Dewan et al. 2017; Oestreicher-Singer and Zalmanson 2013; Ransbotham et al. 2012). However, paid social Q&A platforms charge other users who view answers (i.e., viewers) a small fee (Sun 2017), e.g., RMB 1 or US$ 0.145. Monetized content consumption may differ from consumption of free content (Hoang and Kauffman 2018) which may suffer from the undersupply problem (Goes et al. 2016; Qiu and Kumar 2017). Furthermore, paid social Q&A platforms provide monetary incentives to answerers for answering questions (Technode 2017). The provision of monetary incentives may change the nature of content consumption (Oestreicher-Singer and Zalmanson 2013). Thus, monetized answer viewership and provision of monetary incentives make theories used in extant literature less applicable to the context of paid Q&A.

In addition, unique contextual features of paid Q&A further motivate this study. First, the paid Q&A platform will automatically broadcast questions - but not the answers - to the answerers' followers. This might induce social effects from status or social image-based features (Qiu and Kumar 2017), attracting more content consumption (Dewan et al. 2017). Yet, how such status features will affect the consumption of paid content is unclear. For example, monetary incentives may crowd in/out the effects of status features on content consumption (Berger et al. 2015; James Jr. 2005). Second, the platform can actively engage users with the content (i.e., answers) through content-viewer interactions, i.e., forwards, likes, and comments (Kanuri et al. 2018). It might induce an endorsement effect on answer viewership (Qiu and Kumar 2017). Yet, how such content-viewer interactions work in paid Q&A has not been well understood in the face of a viewership fee.

Motivated thus, this study aims to address two important research questions: (1) *how status features of answerers and content-viewer interactions influence the viewership of answers on paid Q&A platforms?* and *(2) how such impacts on answer viewership will vary as per question price?* To address the research questions, this study uses signaling theory to guide our research model development. Deriving from prior literature (e.g., Levina and Arriaga 2014; Qiu and Kumar 2017), this study conceptualizes answerers' social media status (i.e., membership level) and social media popularity (i.e., follower volume) as indicators of reputation and answer's social favor (i.e., like volume), social diffusion (i.e., retweeting volume), and social feedback (i.e., comment volume) that an answer received as indicators of content-viewer interactions. Overall, this study argues that both cues from answerers and answers will positively affect answer viewership. It further argues that question price will change the effects of various signals on answer viewership.

To test the research model, I track a random sample of questions from Weibo Q&A over time and construct panel data to test the model. Results from the empirical study contribute to the literature in three critical respects. First, this study is one of the first studies to empirically study answer viewership in a paid Q&A site and document several important findings. Second, this study contributes to the theoretical underpinning of signaling theory by validating the dual role of monetary rewards in cue effectiveness. Third, given that prior literature has mainly studied social aspects of consumption of free content, this study examines both the social and economic aspects of paid Q&A on answer viewership. Such findings also have vital implications not only for paid content but also for other contexts (e.g., crowdsourcing) where similar incentives are present.

3.2 Theoretical Background

This section introduces the theoretical foundation of this paper. It first theorizes the research context of paid Q&A and identifies the research gaps that this study strives to address. Next, it introduces the dynamics of the information goods market. Then, it presents the theoretical foundation of this study, i.e., signaling theory. Subsequently, it uses signaling theory to guide the identification of independent variables from related literature. Lastly, it theorizes the moderating role of question price based on prior literature.

3.2.1 Q&A Platforms and Related literature

Q&A platforms can be organized into four categories based on content access cost (paid vs. free) and asker-answerer relationship (social vs. community-based). Table 3.1 presents the typology. On community-based Q&A platforms, there is *no* pre-existing social networking relationship between askers and answerers. Askers post questions to the *unknown* crowd for answers (Wang et al. 2013). Other users up-vote or down-vote to evaluate the quality of answers (Qiu and Kumar 2017; Wang et al. 2013). On social Q&A platforms, askers post questions to their *followees* in their social networking (Liu and Jansen 2018). Answers are evaluated by answer viewers' comments, forwards (sharing), and likes (Kanuri et al. 2018).

Table 3.1 A Typology of Q&A Platforms

		Content Access Cost	
		Paid Content	Free Content
Asker-Answerer Relationship	Social media-based Q&A	Weibo Ask, Fenda.com, Zhihu Paid Consultation	Twitter, Ask Me Anything on Reddit; Zhihu.com
	Community-based Q&A	Quora Knowledge Prizes; TaskCN.com; InnoCentive	Yahoo! Answer, Google Answer

Examples of free community-based Q&A platforms include Yahoo! Answer and Google Answer. Examples of paid community-based Q&A platforms can be Knowledge Prizes on Quora (Baker 2016) and some crowdsourcing platforms e.g., TaskCN (Ye and Kankanhalli 2017). Examples of free social Q&A include Twitter and Ask Me Anything on Reddit.[3] Examples of paid social Q&A include Weibo Ask (textual answers) and Fenda.com (audio answers).

The typology can help better position the paper and pinpoint its contribution to the literature. I use this typology to guide my literature review on online Q&A. A concise literature review in Table 3.2 shows that prior research has mainly focused on the answering behaviors, the quality of answers, as well as answer viewership on community-based Q&A. Three studies (Jan et al. 2018b; Liu and Jansen 2018; Zhao et al. 2018) and several conference papers (e.g., Lim et al. 2017) have focused on social Q&A. Little has examined paid social media-based Q&A. This study intends to fill the literature gap by focusing on answer viewership in paid social media-based Q&A. Departing from these studies, this study theorizes the impacts of both social and economic aspects of paid social Q&A on answer viewership.

Table 3.2 Positioning and Contributions of Study 1 in Q&A Literature

Topics	Paid Q&A	Free Q&A
Answering behaviour (answering volume, response rate, speed, etc.)	Chen et al. (2010); Lee et al. (2013); Jan et al. (2018b)	Buntain and Golbeck (2014); Liu and Jansen (2018); Khansa et al. (2015); Chua and Banerjee (2013); Goes et al. (2016);
Answer quality	Harper et al. (2008); Hsieh and Counts (2009); Teevan et al. (2011)	Lim et al. (2017); Qiu and Kumar (2017); Wang et al. (2013); Chua and Banerjee (2013)
Answer viewership	**This paper**	Ransbotham et al. (2012)

[3] https://www.reddit.com/r/AMA/

On free Q&A platforms, askers post questions to the *unknown* crowd for answers (Wang et al. 2013). On paid Q&A platforms, askers post questions to specific answerers and pay them for answers (Liu and Jansen 2018). Answers are evaluated by answer viewers' comments, forwards (sharing), and likes (Kanuri et al. 2018). Yahoo! Answer is an example of a free Q&A platform. Examples of paid Q&A platforms include Weibo Q&A (textual answers), Zhihu.com (textual answers) (Zhao et al. 2018), and Fenda.com (audio answers).

Both paid and free share a common trait. Their success is a function of traffic (visitors) or viewership, a proxy of perceived Q&A quality (Ransbotham et al. 2012). The higher the perceived quality, the higher the traffic. However, only a paid Q&A platform can: 1) Motivate askers with explicit economic incentives (profits or losses) to submit questions for which viewers are willing to pay; and 2) motivate askers to contribute questions that are perishable (i.e., their value decays with time). This leads to a constant replenishment of the platform inventory of Q&As and higher traffic. I examine both motivations in more detail below.

Economic Incentives for Askers and Answerers

To understand the difference in economic incentives of contributors between the two platforms, we contrast the net present value (NPV) of their expected payoffs (see Table 3.3). Assuming that the reputation effect is not significantly different between free and paid Q&A, the following conditions will influence the decision of contributors: **Askers** would be indifferent between free Q&A and paid Q&A, if the difference between the two NPVs is not economically significant, i.e.,

- *avg. question price paid to answerer* + avg. *share of proceeds from paid viewers ~ 0*

Similarly, **Answerers** would be indifferent between free Q&A and paid Q&A if the difference between the two NPVs is not economically significant, i.e.,

+ avg. question price received from asker + avg. share of proceeds from paid viewers ~ 0

Table 3.3 Comparing Economic Incentives of Contributors between the Two Platforms

	NPV in a Paid Q&A	**NPV in a Free Q&A**
Asker	+ Direct benefit derived from answer - Opportunity cost of developing question + Share of proceeds from paid viewers – Question price paid to the answerer	+ Direct benefit derived from answer - Opportunity cost of developing question
Answerer	+ Reputation effect – Opportunity cost of answering question + Question price received from the asker + Share of proceeds from paid viewers	+ Reputation effect – Opportunity cost of answering question

Based on the data in our sample, the average answerer generates a profit *(+ avg. question price received from the asker + avg. share of proceeds from paid viewers*) of RMB 240.8 per question. This means that if we were to assume that each question represents about an hour's worth of effort, this profit is economically and statistically significantly higher than the RMB 14.11 hourly pay of the average citizen in China ($p<0.001$), as well as the RMB 34.19 hourly pay of the average business professional in China ($p<0.001$).[4] The average asker generates a profit *(- avg. question price paid to the answerer + avg. share of proceeds from paid viewers*)

[4] According to the National Bureau of Statistics of China (2019), the personal disposable income per capita in 2018 was RMB 28,228. Chinese labor laws recognize around 115 days for holidays and weekend breaks, leaving around 250 workdays. Therefore, the average Chinese citizen earns around RMB 14.11 per hour. For business professionals, the average annual salary is RMB 68,380, and the average hourly pay is around RMB 34.19.

of RMB 25.62 per question. This is economically and statistically significantly higher than the hourly pay (RMB 14.11) of the average citizen ($p<0.001$), but lower than the hourly rate (RMB 34.19) of the average business professional. This makes sense since the asker does not need to possess any specific professional skills to ask a question.

In addition to the above, the NPV of askers in a paid Q&A shows that they have a stake in the outcome—they have an explicit economic incentive (question price paid to the answerer) to submit questions for which viewers are willing to pay. If the question they submit does not generate enough paid viewers, they will incur a loss. Overall, the average profit per question for paid Q&A contributors is not only statistically significantly higher than zero, but also higher than the average hourly wage of their respective peers. This means that even though Weibo releases all questions after 90 days, there is a statistically and financially significant benefit that accrues to both asker and answerer.

Content Perishability

Platforms such as Instagram and Snapchat are built on the premise that users want to consume content that is up to date (Pentina and Tarafdar 2014; Tang et al. 2012). Therefore, Weibo's policy of releasing all questions after 90 days is consistent with its goal of replenishing the inventory of Q&As to achieve higher traffic. By enforcing the 90-day limit, it signals that its content is timely and forces contributors to develop Q&As that are perishable. Q&As are perishable if their value decreases (decays) with time. If a Q&A is not perishable, viewers would rather wait and consume it after 90 days, until it becomes free. Hence, the question is: Are the Q&As on the paid Q&A platforms perishable?

If Q&As on Weibo tend to be perishable, we should expect that the interest in these questions (number of paid viewers) should drop dramatically with time. Half-life is a formula used to measure the time required for a quantity (i.e., paid viewers) to reduce to half of its original value, and is commonly used to describe decay. Therefore, the shorter the half-life of a Q&A, the more perishable its nature.

Based on data in our sample (417 Q&As), the average Q&A half-life is around seven days.[5] This means that the value of the Q&As declines very fast and is likely to approach zero well before the three-month release date. Further analysis of the distribution shows that only 18 Q&As have a half-life greater than 12 days. This indicates that over 95% of Q&As lose half of their value before 12 days. Perishable content will lead to a constant replenishment of the platform inventory of Q&As and help achieve high platform traffic. Therefore, evidence based on our sample seems to support our position that Weibo's three-months-to-release Q&A policy is used to motivate the contribution of perishable Q&As.

3.2.2 Dynamic Information Goods Market

In a dynamic market for information goods, the commodity can be exchanged infinitely (Blouin 2003; Janssen and Roy 2004). Although many indicators, such as a good reputation of the seller or the recognized information quality, would mitigate the information asymmetry problem (Ghose 2009), users' willingness on pay for the information goods can be affected by the following two types of situations.

[5] For our calculations, we used the formula shown in Tsay, M. Y. 1998. "Library Journal Use and Citation Half-Life in Medical Science," Journal of the American Society for Information Science (49:14), pp. 1283-1292.

On the one hand, information goods is a type of unique commodity whose value is declining over time. This intrinsic nature of diminishing value undermines users' interest in gaining it. Meanwhile, uncertainty caused by information asymmetries can be reduced (Ghose 2009) by the increasing environmental cues and information leakage. However, if more positive cues manifest its quality, the willingness to purchase the product might be strengthened. Therefore, time is an important determinant of information goods (Ghose 2009; Janssen and Roy 2004; Janssen and Karamychev 2002; Stolyarov 2002).

On the other hand, information goods is experiential. Users can only know its value after they use it (Choudhary 2010). Paying before use is risky. This is especially the case in the context of paid Q&A. Viewers can only know the content after payment. Before deciding to pay for the viewership, users may need to pick up different cues and signals to decide.

Past literature suggests that signalling theory is useful to explain the information asymmetry between two parties and that individuals use the associated signals to make their decision (Connelly et al. 2011). This theory has also been applied to the context of user generated content for online reviews (Riasanow et al. 2015). Furthermore, signalling theory is also a useful lens to study information goods (Bakshi et al. 2014), which will be used in this study.

3.2.3 Signaling Theory

Signaling theory is used to understand how consumers evaluate product quality and make purchase decisions in the face of asymmetrical information (Dawar and Parker 1994; Teas and Agarwal 2000; Wells et al. 2011). For example, Wells et al. (2011) use signaling theory to examine how website quality can be used to signify product quality and affect consumers' intention to purchase on the website. The main mechanism of this theory is the process of signaling that sellers use various signals or cues to reveal unobservable product quality to buyers (Kirmani and Rao 2000).

There are two types of cues or signals in place for sellers to reveal product quality: extrinsic and intrinsic (Richardson et al. 1994). Extrinsic cues are external information related to the product, e.g., price, brand name, retailers' reputation, etc. (Dawar and Parker 1994; Richardson et al. 1994; Teas and Agarwal 2000). Intrinsic cues are internal information about product attributes, e.g., components, ingredients, durability, etc. (Richardson et al. 1994; Yan et al. 2014). Prior literature suggests that extrinsic cues are more readily available or require limited cognition to process (Richardson et al. 1994). As a result, they are more influential to consumers' purchase decisions than intrinsic cues (Richardson et al. 1994; Wells et al. 2011). Intrinsic cues of experience goods are scarce in nature (Wells et al. 2011). Content interactions captured in product reviews are helpful in revealing intrinsic cues of a product (Duan et al. 2008) and influential to consumers' purchase decisions (Aggarwal et al. 2012; Dellarocas et al. 2010; Duan et al. 2008).

In the context of paid social Q&A, answers are a content-related product and a type of experience good (Liu and Jansen 2018; Zhao et al. 2018). Building on past literature (Dodds et al. 1991; Wells et al. 2011), I argue that both extrinsic and intrinsic cues are influential to the answer purchase, i.e., answer viewership. Prominent extrinsic cues include price and sellers' reputation (Dawar and Parker 1994; Dodds et al. 1991), while intrinsic cues include the information conveyed in answer-followers social interaction. Following previous research, in the context of paid Q&A, I try to examine the impacts of such cues as content-viewer interactions, answerers' social media status, and question price, respectively.

Intrinsic Cues in Content-Viewer Interactions

Past literature suggests that social interactions between products and consumers can be captured in various product reviews (Mudambi and Schuff 2010). Reviews can carry internal information about product attributes (Duan et al. 2008; Park et al. 2007; Ye et al. 2019). Hence, reviews are informative for individuals' decisions. Nowadays, many platforms have embedded social interaction functions for users to express their opinions and evaluations via the ways of sharing, liking, and commenting (Kanuri et al. 2018). In the context of content consumption, social interactions between content and viewers are captured in forwarding, liking, and commenting on the content (Dewan et al. 2017; Kanuri et al. 2018).

Content-viewer interactions can provide the content with social endorsement (Dewan et al. 2017; Qiu and Kumar 2017). Usually, content-viewer interactions can help bring the focal content to the awareness of potential consumers and also convey evaluation information about a/the content quality and viewer satisfaction (John et al. 2017a). As a result, the content will be consumed by more users (Oestreicher-Singer and Zalmanson 2013). In the context of this study, answered questions – but not the answers - will be automatically broadcasted to answerers' social networks, which will possibly bring the awareness of the focal question to potential viewers and the resultant answer purchases. In this sense, the *social diffusion*, measured by the retweeting volume, of the focal question determines its exposure to and awareness by potential viewers.[6] In addition, *social favor*, measured by the like volume, and *socal feedback*, measured by the comment volume, will convey users' evaluations about the answer quality. In this sense, social favor and feedback may affect potential viewers' decisions. Hence, following past literature (Dewan et al. 2017; Oestreicher-Singer and Zalmanson 2013; Qiu and Kumar 2017),

[6] Other users can see the answer only after they pay RMB 1 for viewership.

I examine the impacts of received social diffusion, social favor, and social feedback on answer viewership.

Extrinsic Cues by Social Media Status

Past literature suggests that sellers' reputation and brand are important signals of product quality (Dawar and Parker 1994; Teas and Agarwal 2000). This is because consumers can make quality inferences based on sellers' reputations without examining product attributes for every purchase (Dodds et al. 1991). On social media platforms, reputation and status are an asset to social media users (Levina and Arriaga 2014). They usually reflect the market value of a user (Sun and Zhu 2013) and should matter in affecting a potential viewer to pay in order to view an answer. On the social media platform, answerers' social media status reflects the reputation (Levina and Arriaga 2014). In the Weibo platform, membership level indicates an user's social media status, which is based on the amounts of days logging, accumulated use duration, as well as the volume of original posts generated (Ghedin 2013; Zhang and Pentina 2012). Membership level is designed as an indicator of honor (Jiang et al. 2016) and status among platform peers (Goes et al. 2016). It is found that higher level ranks will motivate users to answer more questions in a Q&A platform (Goes et al. 2016).

Answerers' reputation can also be reflected in their popularity on social media platforms. Prior literature has used the number of followers (Metaxas and Mustafaraj 2012; Zhang et al. 2011) or audience size (Barasch and Berger 2014; Qiu and Kumar 2017) to proxy social media popularity. The number of followers can reflect a user's influence as well as popularity in his/her social network (Dewan et al. 2017; Goes et al. 2014b). Social media popularity differs from social media status (i.e., membership level) in that popularity will only be increased by content quality, their expertise or offline fames (Khedher 2015; Levina and Arriaga 2014) while social media status can be increased through tenure duration and contribution level (Goes et al. 2016; Khansa et al. 2015). Past research suggests that users' social media popularity ensures the basic quality level of content, reducing information uncertainty and consumption risk (Goes et al. 2014b; Keller and Lehmann 2006). To some degree, social media popularity presents the influential power of answerers on social media platforms, which may affect the quality of generated content (Levina and Arriaga 2014).

In the paid Q&A market on Weibo, prospective answer viewers would form a strong association between the answerer's social media popularity and answer quality. For example, Weibo only permits prominent celebrities, experts, and opinion leaders to be answerers and charge for answering others' questions (Zhao et al. 2018). Thus, the signals of social media status and popularity can indicate answer quality that will affect answer viewership. In addition, popular users have a strong influence on the content consumption of their followers on social media (Dewan et al. 2017). Thus, I believe popularity may influence the answer viewership in the context of our study.

3.2.4 The Dual Role of Question Price

Prior literature notes the dual role of price: serving as quality cues and monetary sacrifice/cost (Dodds et al. 1991; Yan and Sengupta 2011). On the one hand, price signals quality of the product (Teas and Agarwal 2000), which is found to positively predict the value that the product can provide to customers (Teas and Agarwal 2000; Yan and Sengupta 2011; Yan et al. 2014). As a result, the price can infer product quality and value, which motivate customers' purchases (Wells et al. 2011). Furthermore, prior literature suggests that monetary incentives can present the informational aspect of individuals' competence or performance in solving problems (Deci et al. 1999). The informational aspect will signal participants' competence information and hence the individuals' performance in the focal activity (Ryan and Deci 2002). In the context of paid Q&A, answerers are financially motivated to answer questions. Question price can serve as a signal of answerers' competence in providing high-quality answers and will possibly strengthen the effects of reputation features on answer quality.

On the other hand, the price can reflect the cost/expense or the amount of monetary sacrifice needed to purchase a product (Dodds et al. 1991; Rossi 2014). The sacrifice refers to the amount of money that cannot be spent on other things (opportunity cost), which negatively impacts the perceived product value (Teas and Agarwal 2000). As a result, price negatively affects customers' purchases (Dodds et al. 1991). Another line of the literature suggests that an individual's perception of price fairness is another important factor affecting product purchase (Xia et al. 2004). Price fairness reflects the difference in the quality and costs in product price (Mazumdar et al. 2005). The greater the difference, the lower perceived price fairness. Past research suggests that price fairness will affect the perceived value of a product and hence customers' purchase (Martins 1995; Xia et al. 2004). As argued above, it is intriguing to explore how the question price works in the context of paid Q&A.

3.3 Hypothesis Development and Research Model

We use signaling theory as the overarching theory to guide this study and develop independent variables from related literature. Specifically, I theorize question price, social media status and popularity as extrinsic cues, and social diffusion, favor, and feedback as intrinsic cues. As per signaling theory, such cues provide various signals of answer quality and answer awareness, affecting viewers' purchase of the answers. I further hypothesize that question price will moderate the impacts of multiple cues. The proposed research model is shown in Figure 3.1.

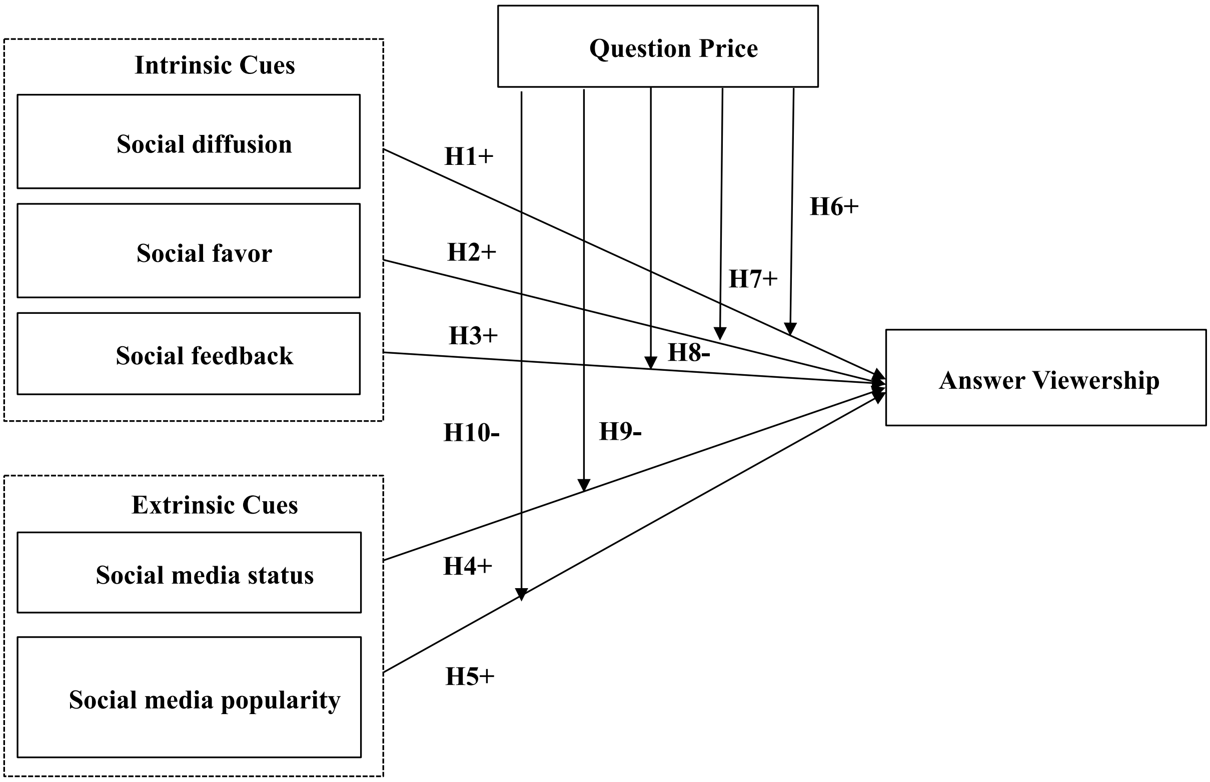

Figure 3.1 Research Model of Study 1

3.3.1 Answer's Social Diffusion

Social media platform empowers users' content to reach a broad audience via social media broadcast function (Gallaugher and Ransbotham 2010). Social diffusion, being captured by the frequency of retweets, demonstrates an actual influence span of the message (Boyd et al. 2010). The greater number of times a question is retweeted or shared, the larger the size of the targeted audience (potential viewers). As a result, the content viewership may increase. Furthermore, users share valuable and/or interesting content within their network. Such sharing or retweeting others' posts to one's own network of followers can be perceived as a type of endorsement that strengthens the credibility of the post (Boyd et al. 2010) and signifies content quality (Lim et al. 2017). As per signaling theory (Connelly et al. 2011), this will increase the sales of the answer, i.e., answer viewership. Furthermore, users will usually add their own opinions when retweeting the post. This adds new value to the original post (Luo et al. 2013), triggering more users to view the content.

Based on the above, I argue that retweeting other's question to ones' own network of followers will increase its exposure and endorse the credibility and quality of its answer, and potentially add new values to the question. As a result, other users will be more likely to pay to view the answer. Thus, I propose

H1. Social diffusion of an answer is positively related to the answer viewership.

3.3.2 Answer's Social Favor

Past literature in social media suggests that socially favoring a post represents an endorsement and referral (Hoffman and Fodor 2010; Lipsman et al. 2012; Naylor et al. 2012). The endorsing increases brand engagement (Aral et al. 2013; Hoffman and Fodor 2010) and may lead to increased product purchase (Lipsman et al. 2012) and content consumption (Oestreicher-Singer and Zalmanson 2013). Besides, social favor, being represented by the number of likes, demonstrates users' satisfaction and positive attitude towards the posts (John et al. 2017a). Firms that integrate the "likes" or "votes" into marketing messages can increase product sales (John et al. 2017b).

Similarly, in the context of paid social Q&A, "likes" may convey positive attitudes towards and satisfaction with answers, which may spur others' consumption. It is similar to the up-votes in community-based Q&A, which is associated with content quality (Chua and Banerjee 2013; Qiu and Kumar 2017). In a similar vein, I argue that social favor an answer receives is a proxy for its quality. Furthermore, such interactive endorsing activities are typically broadcasted to one's own network (John et al. 2017b). This will also increase the exposure of the question and the potential answer viewership.

H2. Social favor of an answer is positively related to its viewership.

3.3.3 Answer's Social Feedback

Past literature suggests that social feedback, being reflected in comments, potentially increases the richness of information related to the product and decreases the information uncertainty (Ghose 2009; Ghose et al. 2007). Feedback can also raise public awareness of the product (Brewer 2001). Consumers are more likely to generate curiosity and interest in something that connects them and satisfies their social gratification (Li et al. 2018; Stokburger-Sauer et al. 2012). As a result, consumers will tend to purchase the products.

In the context of paid Q&A, comments are user-generated feedback given to others' posts on social media (Saboo et al. 2016). It indicates the extent of social interaction with and social attention on the content (Li et al. 2010). Following the above reasoning, I expect that social feedback an answer required help it attract users' attention to the question. As a result, more users will purchase it. Hence, I hypothesize

H3. Social feedback of an answer is positively related to its viewership.

3.3.4 Answerers' Social Media Status

Users' social media status, being demonstrated by the membership level, in Weibo comprises two important parts: contribution level and platform tenure (Zhang and Pentina 2012). It captures answerers' historical performance (Khansa et al. 2015). According to Goes et al. (2016), membership level resides in the status hierarchy of the platform. Status refers to the reputation, respect, prestige, and admiration afforded by others and is a fundamental human motive (Anderson et al. 2015). The link between status and individual behaviors and performance has been empirically validated in various contexts. For example, status is positively related to knowledge contribution in practice communities (Wasko and Faraj 2005), participation on crowdsourcing platforms (Ye and Kankanhalli 2017), as well as mobile apps creation on mobile phone platforms (Kankanhalli et al. 2015). A more relevant study by Goes et al. (2016) found that the desire for status strongly motivates individuals to answer more questions in a Q&A community. The underlying logic is that individuals desiring a higher status will exert a higher effort level (Anderson et al. 2015), which will contribute to performance (Garland 1984; Goes et al. 2016).

In the context of paid Q&A, in order to achieve the goals of a higher level of status on such platforms, users will invest more effort in creating high-quality content (Goes et al. 2016; Khansa et al. 2015). Following this argument, I believe that answerers with a high social media status will contribute high-quality answers to questions in order to maintain their status on platforms like Weibo. In the context of community-based Q&A, membership level has been found to affect the number of answers posted in a Q&A community (Khansa et al. 2015). In the context of paid Q&A, I go further and hypothesize that social media status will motivate individuals to produce high-quality answers. As per signaling theory, such content quality cues by social media status indicate the source credibility, hence persuading viewers to pay for the content (Dawar and Parker 1994; Richardson et al. 1994), i.e., paid answers. Thus, I hypothesize

H4. Social media status of an answerer is positively related to the answer viewership.

3.3.5 Answerers' Social Media Popularity

The number of followers is an informative social signal of popularity and has been used as a proxy of influence (Toubia and Stephen 2013). Past literature has suggested the number of followers determines content consumption (Dewan et al. 2017) and viewership (Kim et al. 2014) as their postings will be automatically broadcasted to their followers. Qiu and Kumar (2017) suggest that having followers will provide individuals image-related utility, which motivates users to contribute quality content to the platform. Barasch and Berger (2014) suggest that as the number of followers increase (audience size increases), users are more likely to be self-focused and avoid activities that may generate negative impressions to their followers. Users tend to be prosocial and produce quality content (Zhang and Zhu 2011) to help maintain their public image. As a result, users with a larger follower size tend to produce high-quality content. Conversely, when owing a smaller audience, users feel that their contributions are not likely to be noticed (Zhang and Zhu 2011) and are less likely to generate quality content.

Following the logic argued above, in the context of paid Q&A, the size of followers will signify the answer quality. As per signaling theory, this will motivate others to pay to view the answer. Furthermore, a large number of followers will increase the exposure of questions to the public. As a result, the user's answers will be viewed by more audiences. Therefore, I hypothesize

> *H5. Social media popularity of an answerer is positively related to the answer viewership.*

3.3.6 Moderating Role of Question Price

Price can provide the signals regarding the quality of the central product (Teas and Agarwal 2000; Yan et al. 2014). These positive price effects, when complemented with the effects from social interactions, are likely to reduce the demand for users' effort in decision making (Wells et al. 2011). Furthermore, the price reflects the desirability concerns of a product (Yan and Sengupta 2011). It will amplify the positive effects of other factors as it arouses consumers' perception of the product desirability (Yan et al. 2014). In the context of paid \Q&A, following this logic, I argue that question price should have a complementary effect with content-viewer interaction, e.g., forward and like, as it reduces decision-making efforts and arouses consumers' perception of product desirability.

Furthermore, question price may convey the information about answerers' competence and may be related to performance (Ryan and Deci 2002), i.e., product quality. This may strengthen the social endorsement from forward and like volumes that an answer received. Following this logic, question price will enhance the impact of social endorsement from the answer's social favor and diffusion. As a result, users tend to purchase the answer. Hence, I hypothesize

> *H6. Question price positively moderates the relationship between social diffusion and answer viewership.*

> *H7. Question price positively moderates the relationship between social favor and answer viewership.*

On the other hand, the price can reflect the cost/expense or the amount of monetary sacrifice needed to purchase a product (Dodds et al. 1991; Rossi 2014). Typically, if a product attracts a large number of social feedbacks, it may be perceived as an indicator that there is something wrong with the focal product (Ghose 2009; Ye et al. 2019). In a similar vein, for a highly priced question, a high level of social feedback may indicate a lower answer quality. This may discourage other users from paying to view the answer. Furthermore, the information conveyed through comments could damage the source for future extrinsic compensations (Jan et al. 2018b). This may pressure toward specified outcomes and regulate their answering behaviors.

As per cognitive evaluation theory (James Jr. 2005), this will crowd out or attenuate the social endorsement effect of social feedback on answer viewership. As a result, I hypothesize

H8. Question price negatively moderates the relationship between social feedback and answer viewership.

In the context of this study, for reputable answerers (e.g., with a high level social media status or social media popularity), charging a high price may cause a negative impression to their followers (Barasch and Berger 2014) (i.e., negative image-related utility). As a result, other users will be less likely to pay to view their answers. Furthermore, a higher question price may lead to the perception of price unfairness (Xia et al. 2004) as answerers of great image can easily profit from advertising on social media platforms (Lipsman et al. 2012). The perceived unfairness may discourage other users from paying to view the answer. Thus, I hypothesize

H9. Question price negatively moderates the relationship between social media status and answer viewership.

H10. Question price negatively moderates the relationship between social media popularity and answer viewership.

3.4 Methodology

3.4.1 Data Collection

I collected data from Weibo Q&A. I wrote a program with Python 3.6 to crawl the web data, employing the keyword search method for obtaining all answered questions. At the first stage, I gathered all newly answered questions and save their URLs for panel data collection. I started data collection on Sep 15, 2017 and obtained all newly answered questions in the following five days, resulting in 536 unique Q&A. I collected the Q&A relevant datasets every three days until Nov 21, 2017, just before all sampled Q&A become free of charge.[7] Each observation records data of Q&A, the answerer, and the asker. In total, I have obtained 23 times of periodic data. After removing those deleted ones during data collection, 417 remained with a panel dataset of 9591 observations.

3.4.2 Variable Measurement

The key dependent variable in our empirical analysis is the answer viewership, each of which is worth RMB 1. It is the number of times that an answer has been viewed.[8] Our major independent variables include various cues. Answerers' cues include social media status and social media popularity. On Weibo Q&A, membership level is a type of honor or level evaluated by Weibo. It is calculated by users' tenure duration and contribution levels (Zhang and Pentina 2012). Thus, I use membership level to measure social media status. Social media popularity is measured by the number of answerers' followers. Answer's social interaction cues include forwards, likes, and comments that the answer receives. I collect data about the number of forwards, likes, and comments and question price directly from the Q&A interface. They capture the constructs of social diffusion, social favor, and social feedback, respectively.

We also include control variables that might impact the dependent variable, including the number of users that the answerer follows, the number of asker's followers, the number of asker's postings, and the number of users that the asker follows. Descriptive information about all variables is listed in Table 3.4.

[7] Postings on social media changes very fast within a week (Patel 2016). I choose every 3 days as the time divider to collect our data since the charging for answers expire within three months.

[8] I are counting each payment as one view. Repeated views by the same viewer are not included.

3.4.3 Model Estimation

I tested the proposed hypotheses with a panel data set. Panel regression model can reduce the collinearity among independent variables and hence improve the estimation accuracy (Hsiao 2014). A Hausman (1978) test is significant ($\chi^2 = 66.54$, $p<0.001$), suggesting that the fixed effects estimation is preferred. Apart from the factors I have focused on, some unobservable factors may confound our results. When these factors are stable over time (e.g., viewers' cultural characteristics), fixed effects panel models (FEPM) can be properly employed to account for endogeneity issues (Wooldridge 2010). Therefore, I estimated a fixed-effects model of the answer viewership. Subsequently, I also employed other estimation strategies, specifications, and adjustments as robustness checks, e.g., two-stage least squares (2SLS) for fixed effect panel model and maximum likelihood estimation (MLE).

Table 3.4 Variable Description and Statistics for Study 1

Variables	Mean	SD	Min	Max
Answer viewership (AV)	284.58	496.18	0	5036
Social Media status (SMS)	40.91	6.56	12	48
Social media popularity (SMP)	1166128	1770421	6928	11784685
Number of users the answerer follows (AFI)	857.49	850.79	31	5912
Social diffusion (SOD)	11.00	24.99	0	376
Social feedback (SOE)	14.67	31.62	0	559
Social favor (SOF)	26.15	61.99	0	957
Number of the asker's followers (ASF)	9941	122431	0	2459823
Number of users that the asker follows (ASFI)	336.17	521.17	0	6529
Number of the asker's posts (ASP)	1059	3078	0	35567
Question price (PRICE)	107.59	249.08	1	2198

Table 3.5 Correlations for Study 1

	1	2	3	4	5	6	7	8	9	10	11
1. AV	1.00										
2. SMS	0.21	1.00									
3. SMP	0.17	0.51	1.00								
4. SOD	0.51	0.20	0.19	1.00							
5. SOE	0.61	0.02	0.13	0.54	1.00						
6. SOF	0.41	-0.07	0.00	0.38	0.52	1.00					
7. PRICE	0.35	0.11	0.06	0.25	0.28	0.20	1.00				
8. AFI	-0.14	0.34	0.24	0.10	-0.18	-0.33	-0.12	1.00			
9. ASF	0.02	-0.02	0.00	0.08	0.02	0.02	0.04	0.03	1.00		
10.ASFI	0.04	0.00	0.05	0.16	0.04	0.01	0.04	0.09	0.56	1.00	
11.ASP	0.07	0.05	0.08	0.11	0.04	0.06	0.09	0.07	0.58	0.52	1.00

Considering data skewness, I have log-transformed all variables. Our dependent variable is *the answer viewership*. The subscript i in the equation represents the paid answer, and subscript t represents the time point. I estimate the following panel data model:

$$AV_{it} = \beta_1 * Log(SMS_{it} + 1) + \beta_2 * Log(SMP_{it} + 1) + \beta_3 * Log(SOD_{it} + 1) + \beta_4 * Log(SOE_{it} + 1) + \beta_5 * Log(SOF_{it} + 1) + \beta_6 * Log(AFI_{it} + 1) + \beta_7 * Log(ASF_{it} + 1) + \beta_8 * Log(ASFI_{it} + 1) + \beta_9 * Log(ASP_{it} + 1) + \mu_i + \varepsilon_i$$

for i = 1, 2,…, 419, and t=1,2,…,23; β is the coefficients' estimates. μ_i and ε_{it} are the random error terms, control for the idiosyncratic effects. Moreover, since question price is a time-invariant control variable, I did not include it in our estimation. I test the moderating effects by mean-splitting the sample into two as per question price.

3.5. Data Analysis and Results

I used STATA 15 to conduct our estimation. The variables description and correlation are shown in Tables 3.4 and 3.5, respectively. To test for multicollinearity, I computed variance inflation factors (VIFs). VIFs for all variables in the analysis ranged from 1.10 to 1.95, ruling out potential multicollinearity problems (Diamantopoulos and Siguaw 2006).

3.5.1 Hypothesis Testing

Since endogeneity issues could exist between answer review cues and answer viewership, I use the number of an answerer's posting as the instrumental variable for this relationship. An answerer who is active in generating original posts and following others will attract other users to retweet, like, and comment his/her postings. However, the posting may not affect the viewership of an answer since other users need to pay to view it.

I applied two-stage least squares (2SLS) for fixed effect panel models (FEPM). Results for fixed effects panel model in Column 2 of Table 3.6 are similar to those for 2SLS EFPM in Column 3 of Table 3.6. The coefficients of independent variables decrease, suggesting that the number of answerer's posting indeed instrument the answer review cues, i.e., like, forward, and comment volume. This suggests our results are robust across estimation methods. Results in Table 3.6 show significant impacts of social media status, social media popularity, social diffusion, social favor, and social feedback, suggesting that H1, H2, H3, H4, and H5 are supported.

Table 3.6 Hypothesis Testing for Study 1

IVs	DV= AV_{it}			
	1	2 (FEPM)	3 (2SLS)	Results
Log (SOF_{it} +1)		0.331 (0.012) ***	0.127 (0.056)*	**H1 supported**
Log (SOD_{it} +1)		0.023 (0.009) **	0.191 (0.086)*	**H2 supported**
Log (SOE_{it} +1)		0.233 (0.012) ***	0.186 (0.029) **	**H3 supported**
Log (SMS_{it} +1)		0.932 (0.036)***	0.858 (0.052) ***	**H4 supported**
Log (SMP_{it} +1)		0.102 (0.009)***	0.062 (0.019) ***	**H5 supported**
Log (AFI_{it} +1)	0.111(0.016)***	0.076 (0.014)***	0.074 (0.017) ***	
Log (ASF_{it} +1)	0.009 (0.004) *	0.002 (0.004)	0.012 (0.007)	
Log ($ASFI_{it}$ +1)	0.006 (0.006)	0.020 (0.005) **	0.038 (0.010)***	
Log (ASP_{it} +1)	0.030 (0.003) ***	0.013 (0.003) ***	0.004 (0.212)	
Fixed Effects	Yes	Yes	Yes	
R^2	0.006	0.333	0.314	
Number of observations	9591			
Significance level: *p <0.05; **p <0.01; ***p <0.001.				

Table 3.7 Comparison by Question Price for Study 1

IVs	DV= AV_{it}			
	Low Price	High Price	Comparison (Δβ, *p*-value)	Results
Log (SOF_{it} +1)	0.289 (0.013) ***	0.562 (0.031) ***	0.273***	**H6 supported**
Log (SOD_{it} +1)	-0.009 (0.010)	0.162 (0.018) ***	0.171***	**H7 supported**
Log (SOE_{it} +1)	0.265 (0.014) ***	0.112 (0.022) ***	-0.153***	**H8 supported**
Log (SMS_{it} +1)	0.848 (0.039) ***	2.068 (0.115)***	1.220***	H9 not supported
Log (SMP_{it} +1)	0.103 (0.014) ***	0.004 (0.015)	-0.099***	**H10 supported**
Fixed Effects	Yes	Yes		
R^2	0.256	0.157		
No. of observations	7498	2093		
Note: • Control variables are included in the analysis but not reported for space limits. • Significance level: ***p <0.001.				

Question price is time-invariant. Since this study adopts the FEPM to examine research model, question price would be omitted from the analysis model. Results of the analysis model without including the main effect of question would lead to a bias for the moderating effects. Besides, correlations between interaction terms may affect the significance of moderating effects (Jaccard et al. 2003). To test the moderating effects of question price, I divide the sample into two groups by question price mean and re-run FEPM, respectively. The results shown in Table 3.7 suggest that H6, H7, H8, and H10 are supported. However, I find that question price positively moderates the impact of social media status on answer viewership. Thus H9 is not supported.

3.5.2 Robustness check

I first lagged all independent variables to *t-1* and re-ran the analysis using the fixed-effects panel model. Results in Column 1 of Table 3.8 are similar to those in Table 3.6, except for the social diffusion. I speculate that social diffusion has a decreasing effect on answer viewership as the endorsement effects of retweeting will decrease quickly (Qiu and Kumar 2017). Comparison results in Column 3 of Table 3.8 is the same as those in Table 3.7. Similarly, the lagged social diffusion impact is not significant in the MLE model.

To further test whether the impacts of independent variables will fade over time. I divide the sample into two by time and re-analyze the data. Results in Table 3.9 indicate that questions tend to be time-sensitive, meaning that users are less motivated to pay to view older questions. Overall, all robustness checks pass.

Table 3.8 Robustness Check for Study 1

Independent Variables	DV= AV_{it}				
	1 (FEPM)	2 (MLE)	3		
			Low Price (FEPM)	High Price (FEPM)	Comparison ($\Delta\beta$, *p*-value)
Log ($SOF_{i(t-1)}$ +1)	0.224 (0.010)***	0.226 (0.010)***	0.205 (0.011)***	0.268 (0.027)**	0.063***
Log ($SOD_{i(t-1)}$ +1)	0.005 (0.007)	0.002 (0.007)	-0.019 (0.008)***	0.036 (0.015)*	0.055***
Log ($SOE_{i(t-1)}$ +1)	0.167 (0.010)***	0.175 (0.010)***	0.193 (0.012)***	0.074 (0.019)**	-0.119***
Log ($SMS_{i(t-1)}$ +1)	0.879 (0.0338)***	0.878 (0.034)***	0.794 (0.036)***	1.342 (0.101)**	0.548***
Log ($SMP_{i(t-1)}$+1)	0.073 (0.008)***	0.073 (0.008)***	0.078 (0.010)***	-0.002 (0.013)	-0.080***
Fixed Effects	YES	No	Yes	Yes	
R^2	0.298		0.239	0.018	
Log Likelihood		11720.36			
Number of observations	9174		7172	2002	

Note: Control variables are included in the analysis but not reported for space limits; Significance level: ***p <0.001.

Table 3.9 Comparison by Time for Study 1

Independent Variables	DV= AV_{it}		
	Stage I	Stage II	Comparison ($\Delta\beta$, p-value)
Log (SOF_{it} +1)	0.480 (0.018) ***	-0.003 (0.012)	-0.483***
Log (SOD_{it} +1)	0.044 (0.011) ***	-0.025 (0.008) **	-0.069***
Log (SOE_{it} +1)	0.221 (0.016) ***	0.105 (0.016) ***	-0.116***
Log (SMS_{it} +1)	0.918 (0.080) ***	0.106 (0.014)***	-0.812***
Log (SMP_{it} +1)	0.174 (0.021) ***	0.004 (0.005)	-0.170***
Fixed Effects	Yes	Yes	
R^2	0.298	0.177	
Number of observations	4587	5004	

Note: Control variables are included in the analysis but not reported for space limits; Significance level: *p <0.05; **p <0.01; ***p <0.001.

3.6 Discussion

The focus of prior literature (e.g., Dewan et al. 2017) has been on content platforms that predominantly rely on advertising fees from the consumption of free content (Kanuri et al. 2018). Departing from existing literature, this study focuses on content consumption in paid social Q&A (i.e., answer viewership). I borrow the general logic from signaling theory and ground more specific theorizing of the model constructs and relationships from related literature. Using unique panel data, I test our model. Results are summarized in Table 3.10. The findings show that answerers' social media status, social media popularity, as well as the answer's social diffusion, social favor, and social feedback positively affect answer viewership. Question price positively moderates the impacts of social diffusion and favor while negatively moderates the impacts of social media popularity and social feedback.

Table 3.10 Summary of Hypothesis Test Results for Study 1

	Expected Sign	Estimated Sign	Significant?
Social Favor	+	+	Yes
Social Diffusion	+	+	Yes
Social Feedback	+	+	Yes
Social Media Status	+	+	Yes
Social Media Popularity	+	+	Yes
Question Price * Social Favor	+	+	Yes
Question Price * Social Diffusion	+	+	Yes
Question Price * Social Feedback	-	-	Yes
Question Price * Social Media Status	-	-	No
Question Price * Social Media Popularity	-	-	Yes

Surprisingly, I find a positive moderating effect of question price on the relationship between social media status and answer viewership. This could be because membership level is accumulated through experience and contribution (Goes et al. 2016) and conveys answerers' competency. Such information will arouse the informational aspect of question price instead of the controlling aspect. As per cognitive evaluation theory, it may strengthen the impact of membership level. Unlike having a large number of followers, one may not be able to readily cash out the influence of membership level (Levina and Arriaga 2014). Those with a large number of followers can easily cash out their influences by posting sponsored advertisements in their own network (Jin and Phua 2014). Users may look less upon those with a large number of followers who set up a high question price.

Nevertheless, the findings should be interpreted in terms of its limitations. First, I have not studied the process of question answering. I cannot capture the amount of effort that answerers have put in answering. Future research can explore what makes answerers contribute high-quality answers. Furthermore, future research can study how answerers determine the price to charge for their answers. It is still unknown what the optimal pricing strategy is for such content. Second, the research is conducted at a question-answer level. Future research should explore this phenomenon from a platform perspective, i.e., whether such a function will increase users' interactions. Third, the data I used to test the research model is sufficient but limited. Future research can collect more data from this site and validate whether our findings still hold. Fourth, I only focus on the volume of the comments instead of their sentiment. Future research can conduct a textual analysis on the comment sentiment and examine its impact on answer viewership.

3.6.1 Theoretical Contribution

The findings contribute to the existing literature in three significant ways. First, this study contributes to the content consumption literature (Dewan et al. 2017; Kanuri et al. 2018;

Oestreicher-Singer and Zalmanson 2013) by focusing on paid content. To the best of my knowledge, this study is the first attempt to quantify the impact of various cues on answer viewership. This is very important because, in paid Q&A, viewership is directly related to revenue generation for question asker, answerer, and the platform. In addition, although prior research has focused on content viewership (Ransbotham et al. 2012), answer/content quality (Blohm et al. 2016; Chua and Banerjee 2013; Qiu and Kumar 2017), and answering behavior (Khansa et al. 2015), very few studies have investigated how answerers' social features and question price affect answer viewership. Furthermore, prior research studied content consumption in a community-based Q&A (Goes et al. 2016; Ransbotham et al. 2012). Departing from past research, this study examines the impact of social networking features. The unique setup in paid Q&A highlights the importance of individual-level social effects (i.e., social media status and popularity) and answer-level social effects (i.e., social diffusion, favor, and feedback) on answer viewership. As a result, our study enriches existing Q&A literature by finding the importance of social networking features.

Second, extant literature has examined only the social effects on content consumption (Dewan et al. 2017; Goes et al. 2016; Oestreicher-Singer and Zalmanson 2013). This study extends this literature by exploring both the social effects (e.g., reputation features and social interactions) and economic effects (e.g., question price) on answer viewership. The results indicate that question price can present a dual role, i.e., both negative and positive moderating effects. In addition, this contributes to the literature by suggesting that the link between social effects and content consumption is more complicated than expected Dewan et al. (2017).

Third, consistent with prior literature (Qiu and Kumar 2017; Toubia and Stephen 2013), I confirm the social endorsement effect by finding that answer's social diffusion, social favor, and social feedback positively affect answer viewership. More specifically, I find that question price positively moderates the impacts of social diffusion and social favor but negatively moderates the impacts of social feedback. This suggests that the social endorsement effect of different answer features vary by monetary incentives. As a result, these findings help us modify our understanding of how social endorsement could take effect in paid social Q&A.

Fourth, this study applied signaling theory to paid Q&A market for discovering useful signals. To the best of my knowledge, prior literature attempted to employ this theory in various settings (Wells et al. 2011) but not in paid Q&A where cues are embedded within social interactions. This has extended the applicability of signaling theory to an emerging but important context. Furthermore, by integrating prior related literature with signaling theory, this study contributes to the literature by identifying the interactions among cues. Fifth, this study also contributes to growing information systems literature on Q&A (Goes et al. 2016; Qiu and Kumar 2017) by developing a context-specific framework for paid social Q&A, identifying unique constructs and relationships predicting answer viewership. This research fills gaps in the understanding of this new phenomenon.

3.6.2 Managerial Implications

This study has several important managerial implications. This study sheds light on the possibility that social media platforms such as Facebook and Twitter may be able to switch from an ad-revenue dominant business model (Oestreicher-Singer and Zalmanson 2013; Sun and Zhu 2013) to the content commercialization business model. The findings provide guidelines to such social media platforms on how to monetize users' content for profit. In particular, social media platforms should encourage content producers to strengthen and improve various signals that are conducive to viewership. First, platforms may direct their marketing strategy towards these identified and examined attributes. For example, since the membership level of the answerer on Weibo has a significant effect on answer viewership, it is critical to building an effective level-ranking mechanism. Second, the interaction and endorsement from other users on the answer are shown to be important to answer viewership. Platform managers can encourage viewers to engage in the interaction and raise the awareness of answers in public.

Additionally, platform managers should regulate the price setting for answerers. They can provide guidelines to answerers regarding the pricing strategy for enhancing their social image. As suggested in our study, the effect of question price on viewership is not monotonic. Depending on the context, it may increase or decrease viewership. Platforms may want to inform their answerers of such effects so that they can incorporate them when setting the question price. Furthermore, it may be advisable for platform managers to design internal controls for the content commercialization mechanisms to avoid any plagiarism and content theft, which will discourage answerers from providing high-quality answers.

This study also provides insights into UGC platforms. It suggests that financial incentives could be important for users to engage in generating quality content. For example, Burtch et al. (2018) note that providing financial incentives is conducive to the quality of generated reviews. Furthermore, incorporating social networking into user-generated content platforms could help improve content generation. Qiu and Kumar (2017) and Huang et al. (2017) document that incorporating social networking can help increase the quality of content generated. In sum, this study highlights the importance of incorporating social network features (membership level and social media popularity) and answer's features (forward, like, and comment volume) to the design of an effective paid Q&A system.

3.7 Conclusion

Given the growing popularity of digital content, this study focused on paid social Q&A. More specifically, I drew upon the signaling theory to examine the impacts of different signals on the viewership of a paid answer. Referring to social media, online reviews, and cognitive evaluation theory literature, I investigated signals from multiple sources, including the answerer and answer-viewer interactions to the paid answers. In addition to this, I further compared the impacts of signals by question price. I found social effects of answerers' social network features in terms of membership level and social media popularity and answer-viewers interactions in terms of forward, like, and comment volumes. Interestingly, question price moderates such effects. Our findings provide managerial suggestions to social media platforms on how to improve the management of content commercialization and indicate that a switch from an ad-revenue-based business model to content monetization might be an economically viable option.

CHAPTER 4 STUDY 2: TOWARD PROFITABLE QUESTIONS ON PAID Q&A: A PERSPECTIVE FROM QUESTION FRAMING

4.1 Introduction

Paid Q&A services have been increasingly popular in recent years as a practical approach to acquire quality information (iResearch 2018). A survey of 2,000 people about their attitudes towards paid Q&A service suggests that 74 percent of them are willing to pay for an answer, and 66 percent have paid before (Custer 2016). Although numerous competitors have attempted to launch Q&A systems and monetize content ambitiously, most of them were eventually dismal to leave, even for leading companies. For example, Google ceased Google Answers in 2006 and Google Helpouts in 2015, and LinkedIn ceased LinkedIn Answers in 2013. Recently, social media platforms, e.g., Zhihu.com and Weibo.com, launch a novel paid Q&A service, authorizing online celebrities (answerers) to answer users' (askers) questions for a profit (question price). They also enable all users (viewers) to pay a small flat fee to view the answer to one question. This novel revenue model offers users more channels and fewer barriers to gain answers, boosting the economic value of the paid content.

This study aims to investigate the linguistic power of the question content in boosting the economic value of the answer at a premium (i.e., profitability). Three critical aspects motivate this research. First, askers are incentivized to frame the question content in paid Q&A. Prior studies have suggested that financial gain (i.e., profit), as one type of extrinsic motivation, incentivizes people to engage in social media (Emerson 1976; Oh and Syn 2015), such as paid Q&A platforms. People participate in social media with various motivations (Calic and Mosakowski 2016). On the one hand, paid Q&A attracts askers to seek customized advice from people they favor. It satisfies askers' cognitive needs (e.g., information seeking) (Choi and

Shah 2017) and affective needs (e.g., self-enhancement and social support) (Choi and Shah 2016; Zhao et al. 2020). On the other hand, askers are also financially driven to make a profit from the questions they ask (Jan et al. 2018b; Zhao et al. 2020). Thus, askers are rational profit pursuers on paid Q&A. Being one of the beneficiaries of the paid Q&A service, askers would have a closer identification with other stakeholders (the answerer and platform) who share the profit and tasks (Q&A) for which they work (Estrin et al. 1987). In this case, askers may increase their participating efforts and create valuable questions (Roberts et al. 2006).

Second, paid Q&A is a new emerging revenue model, the profitability of the paid question is less explored. Existing online Q&A literature focuses much on studying the answerer and asker's participation motivations (e.g., Fang and Zhang 2019; Khansa et al. 2015; Zhao et al. 2016; Zhao et al. 2019; Zhao et al. 2020), the indicators of the answer quality (e.g., Chua and Banerjee 2013; Fichman 2011; Harper et al. 2008; Jeon et al. 2006; Zhang et al. 2019b), and the factors impacting the consumption of free answers (e.g., Jin et al. 2016; Ransbotham et al. 2012). A few research has attempted to investigate the consumption of paid answers (Cai et al. 2020; Yang and Ye 2019). They identified and examined many non-textual characteristics of the answerer (e.g., follower volume and membership level), the answer (question price and prior sales), and the consumer-answer interactions (e.g., like and comment volume). However, there is a lack of empirical studies uncovering the role of textual characteristics.

Third, IS literature has paid a lot of attention to the textual characteristics of the online content that describes physical products. Studies on digital products are rare, and none have been conducted for paid answers. For example, substantial studies have examined that online review content is crucial for the sales of products on electronic commerce websites (e.g., Archak et al. 2011; Ghose and Ipeirotis 2011; Pavlou and Dimoka 2006). Recent studies found that the advertising and comment/review content published in social media can significantly influence the sales of physical products (Bapna et al. 2019; Goh et al. 2013; Lee et al. 2018). It has also been noted that textual information about a movie and news article can predict their sales (Berger and Milkman 2012; Eliashberg et al. 2007). Similarly, for one paid answer, prospective viewers can evaluate the interests and user relevance from the question description to make purchase decisions. Insofar as prospective viewers have to process the information embedded in the question content before payments, it is unknown that what and how qualitative information of the question content impacts their purchases.

To address the above knowledge gaps, this study draws upon social presence theory to capture the informative impact and affective impact of the question content on the asker's profit. The concept of 'social presence' is closely related to 'immediacy' and 'intimacy' (Argyle and Dean 1965; Wiener and Mehrabian 1968), explaining the degree to which a medium (the question content in this study) facilitates the recipient's awareness of the existence of the sender and understanding of the delivered message (Miranda and Saunders 2003). In the light of answer invisibility, a well-framed question would bring prospective viewers trust in the answer quality (e.g., the relevance and helpfulness of the answer) by promoting their perception of social presence on the stories shown in the question (Huang et al. 2017). Specifically, an informative question empowers online users to have meaningful and insightful learning about the question (Goh et al. 2013), the process of which helps them integrate information into cognitive structures about the answerer and the potential answer (Ausubel 1963). While an affective question attracts users' attention and reinforces the event and situation that an asker encountered mainly through the usage of emotional words (Ludwig et al. 2013). Therefore, our research question is: *What linguistic features of the question content create informative and* *affective impacts in paid Q&A, respectively, and whether and how do they matter to the asker's profit?*

To answer the research question, this research collected a random sample of 9,223 unique fee-charged questions from Weibo Q&A from March to November 2019. Weibo Q&A belongs to one of the most popular social media platforms in China, Sina Weibo, and was launched in December 2016. Sample questions in this study were published during the period between March and August 2019. This research used a text analysis tool, Linguistic Inquiry and Word Count (LIWC) software[9], to construct measures that operationalize the informative and affective characteristics of the question content. Results from the empirical analysis showed that the rich and cognitive information embedded in the question content has a negative quadratic relationship with the sales of an answer, showing an evidence of the informative impact. While the extreme emotions embedded in the question content have a positive relationship with the sales, examining the affective impact.

This study makes the following contributions to IS literature. First, it complements the void of social media research, especially for paid Q&A research, in content monetization through studying the qualitative information (i.e., textual content of the question). Second, this research identifies the informative and affective nature of the paid content and examines their influence on the sales of paid content, which enhances our understanding of the content consumption behavior. Third, the findings validate the criticality of the informative impact of social media content on purchase behavior by showing a negative quadratic relationship, which challenges the linear effect that prior research finds (e.g., Archak et al. 2011; Eliashberg et al. 2007; Goh et al. 2013).

[9] http://liwc.wpengine.com/

4.2 Theoretical Background

This section offers the literature review of researching linguistic features in online consumption. Then, it introduces the theoretical foundation of this study, i.e., social presence theory.

4.2.1 Paid Q&A and Question Framing

Social media has been the most favorable channel to advocate the image of a brand and drive the sales of a product by increasing user engagement (Goh et al. 2013; Huang et al. 2017). As a result, platform practitioners have capitalized on the affordance of social media and launched various business models on it to boost the economic value of UGC, e.g., brand communities (Goh et al. 2013), advertising (Zhang et al. 2016), paid subscription (Bapna et al. 2018), and pay-per-item (Kim et al. 2018). Paid Q&A is a pay-per-item business model in which social media users make the payment for an answer.

Paid Q&A adopts the profit-share scheme, which receives increasing attention from practitioners and scholars (Jan et al. 2018b; Ma and Zhang 2019; Yang and Ye 2019; Zhao et al. 2020). On such a new paid Q&A platform, the asker, answerer, and answer viewers constitute a tripartite relationship. One user (asker) pays another user (answerer) for obtaining an answer to a personalized question, and other users (viewers) can pay a smaller flat fee to view the answer. The asker and answerer share the revenue from the answer viewership. Answerers are usually social media influencers with a considerable number of followers on the platform. Instead of paying for asking a question, it is more affordable for viewers to pay a smaller viewing fee and saves effort in framing a question. More importantly, the profit-share scheme empowers an asker to profit from the paid Q&A service.

Prior studies have suggested that financial gain (i.e., profit), as one type of extrinsic motivation, incentivizes people to engage in social media (Emerson 1976; Oh and Syn 2015), such as paid Q&A platform. People participate in social media with various motivations (Calic and Mosakowski 2016). On the one hand, paid Q&A attracts askers to pay for seeking customized advice from people whom they favor. This satisfies askers' cognitive needs (e.g., information seeking) (Choi and Shah 2017) and affective needs (e.g., self-enhancement and social support) (Choi and Shah 2016; Zhao et al. 2020). On the other hand, askers are also financially driven to make a profit from the questions they ask (Jan et al. 2018b; Zhao et al. 2020). Thus, askers are rational profit pursuer on paid Q&A. Furthermore, being one of the beneficiaries of paid Q&A service, askers would have a closer identification with other stakeholders (the answerer and platform) who share the profit and tasks (Q&A) for which they work (Estrin et al. 1987). In this case, askers may increase their participating efforts (Roberts et al. 2006).

This study aims to explore what endeavors askers can do to maximize their financial gain. Prior scholarly investigations found that content producers tend to tailor their content for catering to consumers when incentivized by financial gain (e.g., Guo et al. 2017; Lee et al. 2018; Sun and Zhu 2013). On paid Q&A, viewers cannot evaluate the quality of the answer before making the payment, which creates an uncertain consumption context. However, a well-framed question may solicit many prospective viewers through increasing their perceived value of viewing the answer. It supports people to have meaningful and insightful learning about the story in the question, the process of which helps them integrate information into cognitive structures about the answerer and the potential answer (Ausubel 1963).

Despite an increasing number of social media platforms that adopt this emerging business model, such as Weibo and Zhihu (Zhao et al. 2018), it has attracted little academic attention on the askers' effort and financial gain. Existed Q&A literature has mainly investigated answerers and askers' participation motivations (Jin et al. 2015; Khansa et al. 2015; Zhao et al. 2020) and answer quality criteria (e.g., Fichman 2011; Kim and Oh 2009; Lou et al. 2013). However, a paid Q&A will be only viable when askers desire to participate (Sun and Zhu 2013). And, given the consumption market with visible questions and invisible answers, it is vital to know what characteristics of the question content, which is not only used to communicate with answerers but also the way to attract prospective answer viewers, help askers to gain a profit. Thus, this research attempts to fill such a gap from the perspective of question framing.

4.2.2 Prior Research on Linguistic Features

Considering the massive content online, one crucial literature stream contributing to the economic value of the content is on how linguistic features of the content impact users' attention and perception and ultimately influence content consumption. As summarized in Table 4.1, prior research focused on identifying linguistic features of three types of content. The majority of studies focused on online reviews about physical products, examining that several linguistic features influence the perceived helpfulness of the review and the economic value of the product (e.g., price, sales, and expenditure) (e.g., Goh et al. 2013; Pavlou and Dimoka 2006; Yin et al. 2014).

The second type of content is social media posts that describe external services or products. Research efforts focused on investigating the impacts of various post characteristics on user engagement, including likes, comments, shares, and click-throughs (e.g., Bapna et al. 2019; Lee et al. 2018; Yang et al. 2019). Other research focused on the textual content that is the final place of individuals' consumption, such as news articles (Berger and Milkman 2012; Heimbach and Hinz 2016), answers (Zhang et al. 2019a), and social media posts (Han et al. 2020), and explored relationships between textual features and user response.

A review of past literature (e.g., studies listed in Table 4.1) helps this research identify the research gap and conduct research. Qualitative variables appearing in the literature mainly consist of the text length, valence, and other contextual features. On the one hand, contextual features that existing research identifies are contingent upon various marketplaces and/or products that are the research context. For example, benevolence and credibility that consumers perceive from online reviews are critical for building trust in an online auction market (Pavlou and Dimoka 2006). For electronic products (e.g., digital camera), reviews that include positive descriptions of the product's specifications (e.g., amazing picture quality, good battery life) will attract consumers to purchase the product (Archak et al. 2011). And then, in online brand communities, the disclosure of brand-relevant attributes (e.g., philanthropy, kindness, achievement, credibility) will increase user engagement and ultimately improve the sales of products (Bapna et al. 2019; Lee et al. 2018). Thus, it is critical to identify meaningful linguistic features based on the specific research context.

In paid Q&A, users pay for an unknown answer in social media. A well-framed question should deliver helpful information about the answer and also trigger viewers' interest in the answer. Two linguistic features of the question content might be significant for attracting viewers to pay for an answer, i.e., question informativeness and sentiment extremity. They reflect the informative support and affective support of the question content, respectively. Question informativeness here refers to the level of the detail to which askers describe their problems. Sentiment extremity means the level of intensity to which askers exhibit extreme emotions in their question content.

On the one hand, a question with rich information can enable the problem that the asker has clear to viewers, so viewers can judge their demands to the answer. On the other hand, in social media, users are keen on content with the emotional appeal (Goh et al. 2013; Kim and Oh 2009; Yang et al. 2019; Zhang et al. 2019a), especially for extremely negative content (Yang et al. 2019; Yin et al. 2014; Yin et al. 2021). I will offer more elaborations on them in the next section.

Table 4.1 Previous Empirical Research Examining the Impacts of Linguistic Features of Online Content on Users' Attitudes and Behaviors

Content	Study	Constructs	Method	Key Findings
Online reviews about physical products	Pavlou and Dimoka (2006)	Independent Variables • Benevolence • Credibility Dependent Variable • Price premium	Secondary data of 10,000 comments of 420 sellers and survey data of these sellers' customers in eBay's online auction market **Unit of analysis**: Seller level	**Linear effect** The benevolence and credibility contained in the sellers' previous comments can engender customers' trust and hence create price premiums for sellers.
	Forman et al. (2008)	Independent Variables • Review valence • Reviewer identity disclosure • Shared geographical location Dependent Variables • Sales • Review helpfulness	Secondary data of reviews of 786 unique books on Amazon.com **Unit of analysis**: Product level	**Linear & moderation effect** Disclosing reviewers' identify-descriptive information in reviews increases perceived review helpfulness and future sales. Equivocal content (neither extreme positive nor negative) enhances the effect of identity disclosure on the review helpfulness.
	Archak et al. (2011)	Independent Variables • Review length • Product-relevant decriptions, e.g., picture/video quality, size, ease of use, battery life, and design of the digital camera Dependent Variable • Sales	Secondary panel data of 41 unique digital cameras and 19 unique camcorders on Amazon.com **Unit of analysis**: Product level	**Linear effect** Review length has a negative effect on sales. For the text-based information in reviews, consumers will prefer to purchase a camera of which reviews contain positive descriptions, such as "amazing picture quality", "great picture quality", "simple ease of use", "great design", "good battery life", etc.

	Ghose and Ipeirotis (2011)	Independent Variables • Review subjectivity • Review readability • Proportion of spelling errors Dependent Variables • Sales • Review helpfulness	Secondary panel data of 411 products on Amazon.com **Unit of analysis**: Product level	**Linear effect** Extreme subjective and a mixture of objective content in reviews decrease product sales but increase review helpfulness. Review readability measured by Gunning Index increases both review helpfulness and sales, and spelling errors decrease them.
	Goh et al. (2013)	Independent Variables • Information richness • Valence Dependent Variable • Expenditure	Secondary panel data of 398 consumers in a business's Facebook business page **Unit of analysis**: Consumer level	**Linear effect** Reviews' information richness (i.e., number of concepts), net positivity increase consumers' expenditure.
	Yin et al. (2014)	Independent Variables • Emotions in the review • Review length • Review readability Dependent Variable • Review helpfulness	Two experiments on 78 undergraduate students at a southern U.S. university and secondary data of 187,675 reviews in Yahoo! Shopping **Unit of analysis**: Review level	**Linear effect** Reviews indicating anxiety emotion are more helpful than those displaying anger emotion. Review length and readability measured by Coleman-Liau Index increase the review helpfulness.
	Yin et al. (2021)	Independent Variables • Anger emotion • Review valence Dependent Variables • Review helpfulness • Attitude toward the target	Six laboratory experiments on participants with reviews in Yahoo! Shopping **Unit of analysis**: Review level	**Linear & moderation effect** Anger emotion in the negative reviews decreases review helpfulness and enhances the impact of negative reviews on people's attitudes to purchasing.
Social media posts about external products	Lee et al. (2018)	Independent Variables • Description of the brand personality • Disclosure of informative cues Dependent Variables • Likes • Comments • Shares • click-throughs	Secondary data of 106,316 unique posts in 782 companies' Facebook business pages **Unit of analysis**: Post level	**Linear & moderation effect** The inclusion of more brand personality-relevant content increases user engagement, but the inclusion of more directly informative content (e.g., price and deals) decreases that. Brand personality content weakens the negative effect of directly informative content.
	Yang et al. (2019)	Independent Variables • Post valence • Post content, e.g., complaint, customer question and	Secondary data of 10,681 posts in 39 companies' Facebook business pages	**Linear effect** Positive and negative posts receive more likes than and similar comments as neutral posts but fewer likes and

		suggestion, irrelevant message. Dependent Variables • Likes • Comments	**Unit of analysis**: Post level	comments than negative posts. Various post content has a significant impact on likes or/and comments to various extents.
	Bapna et al. (2019)	Independent Variables • Firm credibility • Professional organizing • Organizational achievement • Seeking opinions Dependent Variable • Likes	Secondary panel data of 9,470 posts in 15 companies' Facebook business pages **Unit of analysis**: Post level	**Linear effect** Posts that convey the firm credibility (e.g., knowledge of the product and industry), organizational achievements (e.g., firm partnerships, awards, milestones), offers or promotions, and seek opinions receive more likes.
Content as target per se	Berger and Milkman (2012) and Heimbach and Hinz (2016)	Independent Variables • Emotions • Valence Dependent Variable • The likelihood of making the most e-mailed list	Secondary data of thousands of articles on the NYT website **Unit of analysis**: article level	**Linear effect** Positive articles have a higher likelihood of making the most e-mailed list than negative articles. High-arousal positive (e.g., awe) and negative (e.g., anger, anxiety) emotions increase the likelihood.
	Zhang et al. (2019a)	Independent Variables • Succinct paragraph structure • Typographical cue • Metaphor • Example count • Citation count • Humor • Confidence Dependent Variables • Popularity • Perceived professionalism	Secondary data of 1,150 answers to 23 questions in Zhihu.com **Unit of analysis**: answer level	**Linear effect** Succinct paragraph structure, humor, and example count of the answer increase its popularity. Confidence, example count, and citation count of the answer increase its professionalism.
	Han et al. (2020)	Independent Variables • Post content characteristics, e.g., valence, length, topic, inclusion of image, hashtag, link, mention, etc. Dependent Variable • Virality	Secondary data of 799,943 posts on Twitter **Unit of analysis**: Post level	**Linear effect** Post length, the inclusion of images and videos in the post, humor, and emotion increases post virality. However, Positivity and the inclusion of hashtags decrease the post virality.

4.2.3 Social Presence Theory

With the dominance of computer-mediated communication, an increasing number of studies have been investigating factors that affect the perception and behavior of human beings through electronic media. One important literature stream develops on the social presence theory (Short et al. 1976). Traditionally, social presence is "the degree of salience of the other person in a mediated communication and the consequent salience of their interpersonal interactions" (Short et al. 1976, p.65). Social presence theory has been used to explain the telecommunication medium's influence and performance (e.g., Brown et al. 2010; Harrison 2018). Meanwhile, researchers have also applied this theory to a broader of research areas, including user-website interaction (Kumar and Benbasat 2006; Qiu and Benbasat 2009), user-virtual agent interaction (Hess et al. 2009; Köhler et al. 2011), and user-advertisement interaction (Coyle and Thorson 2001; Fortin and Dholakia 2005).

IS literature has adopted social presence theory to explain how textual features of UGC impact consumers' perception and behaviors (e.g., Huang et al. 2017; Pu et al. 2020). In the context of information exchange, users' perceived interpersonal interactions that one piece of content supports decides the degree of social presence (Kehrwald 2008). It has been found that content providers can enhance audiences' perceptions of social presence through framing the content to be socially vibrant and polite (Gefen and Straub 2003), emotive and media-rich (e.g., the using of emoji) (Cyr et al. 2009), and interactive and live demonstrative (Qiu and Benbasat 2009). Previous literature suggests that informative and affective information disclosed by the content can elicit consumers' cognitive processing and shorten their psychology distance with the storyteller (e.g., asker) as well as the relevant story (Stieglitz and Dang-Xuan 2013). For example, Pu et al. (2020) found that the identify information disclosed in the reviews increases consumers' social presence about the review provider and the product. Affective information has salient contagion effect on individuals, has been substantially proved to facilitate social presence (Ott 2017; Wang et al. 2020). In the paid Q&A context, given that the answer is inaccessible before payments, prospective viewers evaluate the answer helpfulness and quality from information contained in the question. A well-framed question can allow prospective viewers to experience the asker's situation and question as being psychologically present (Sia et al. 2002). Linguistic features contained in the content could influence users' trust, perceived enjoyment, and usefulness, and hence their consumption intention and decision (Harrison 2018).

Therefore, from the perspective of social presence, to persuade viewers to purchase the unknown answer, the asker should treat the question content as a medium that can communication helpful and contagious information with viewers through the question description. Question informativeness and sentiment extremity may alter the level of social presence of the question content, thereby changing viewers' desire to pay for it. First, question informativeness helps prospective viewers construct a rational cognition to the uncertain answer (Bleier et al. 2019). The asker can draw as much resourceful and helpful information as possible into the question description, such as the answerer's characteristics, problem details, and other relevant information practices. The question informativeness could help viewers recognize the asker's intention (Mangold and Pobel 1988), creating them a social interaction opportunity. Moreover, details and cognition-relevant words can elicit viewers' mental processes on similar experience and memories, hence increasing their social presence. As a result, answer viewers, as the third-part observers, can perceive a strong desire for learning the solution to the problem.

Second, sentiment extremity evokes prospective viewers' affective mental processes (Huang et al. 2017). As online questioning and answering is a way of human communication, the question content often conveys information about the asker's emotional state at the time of asking (Bollen et al. 2011). Askers portraying an extreme sentiment in their question content may create a virtual experience of involving in the question-and-answer period for viewers. Past literature has shown that emotionally charged content is perceived to be contagious (Ott 2017; Wang et al. 2020), negative biased content indicates a more comprehensive thinking on relevant events (Yin et al. 2014). Such types of social cues will improve prospective viewers' perceived intimacy. Thus, sentiment extremity embodied in the question content may shorten the potential viewers' perceived social distance from the asker and answerer (Pavlou et al. 2007).

4.3 Research Model and Hypotheses

Figure 4.1 shows our research model of understanding the impact of content features of the question content on askers' financial gain.

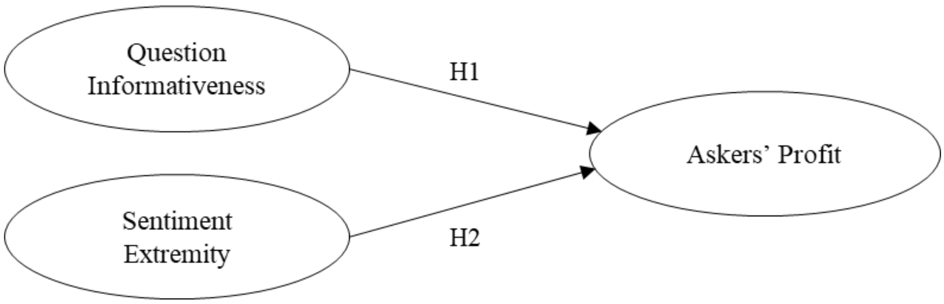

Figure 4.1 Research Model of Study 2

4.3.1 Question Informativeness

Question informativeness refers to the degree to which an asker elaborates on the question (Cooke et al. 2002). In the marketing literature, informativeness about a product is the primary cognition that customers require for evaluating the functional aspect and value of the product

(Verhoef et al. 2009). This fact-based cognition to the question can alleviate prospective viewers' uncertainty about the answer quality and improve their attitudes toward an unknown answer. Askers can provide detailed information pertaining to question-relevant backgrounds, situations, confusions, objectives, as well as answerers' competency in solving the problem. After reading a question with fully informational support, prospective viewers would have conscious mental processing. And then they would have strong desire to know other's (answerer) solutions.

Additionally, in the paid Q&A, a social networking site, information richness increases recipients' perception of sufficiency, reliability, and immediacy to the content (Shang et al. 2017). The spatial and temporal separation of online content consumption creates information asymmetries, which is a disadvantage for answer viewers. However, askers can help viewers to overcome this problem by providing resourceful and helpful information in the question content. Viewers may learn about the features of the question content and answerer from the asker's description.

However, the relationship could be more nuanced than the above assumption. A high level of question informativeness may not assure the description quality. A quality narration requires askers with excellent effort and capabilities to put questions in words logically and attractively. However, Internet users tend to post their content in a long-winded way (Tate 2018). Those questions may contain redundant, irrelevant, and overspecified content, which can switch off readers' interest. Besides, overspecified questions may be quite personal such that others may lose interest. By contrast, a well-organized and clearly-expressed question should give answer viewers some wiggle room. Combining the preceding arguments, I expect that the question informativeness will show an inverted U-shaped relationship with the odds that the asker profits from this question. Thus, I hypothesize:

> *H1: Question Informativeness has an inverted U-shaped (negative quadratic) relationship with the askers' profit.*

4.3.2 Sentiment Extremity

Internet users' reactions to emotional content are complicated. Researchers investigate such impacts with different measurements, including the valence of monotonous emotions (i.e., positive or negative sentiment) (e.g., Berger and Milkman 2012; Chen et al. 2019b), the net valence of positive emotion (i.e., positive emotion valence – negative emotion valence) (e.g., Huang et al. 2019), and net valence of negative emotion (i.e., negative emotion valence – positive emotion valence). In this study, sentiment extremity pertains to the third type, the status of averaged negative sentiment.

In the social networking community, people prefer to pay for content with a high level of sentiment extremity. An expression with strong negative emotion can help viewers make sense of the content provider's experience, offset dissonance, and enhance social connections (Peters and Kashima 2007). It has also been noted that emotionally coded content could evoke people's high-arousal reactions, such as interest and curiosity (Berger and Milkman 2012), and increase their engagement in the debate (Stieglitz and Dang-Xuan 2013). Moreover, people tend to use extremely emotional words (e.g., cried, worry, desperate, and hopeless) to express themselves when they encounter urgent and thorny difficulties. Such events have a high power of drawing Internet users' attention and arouse their empathy (Stieglitz and Dang-Xuan 2013). In paid Q&A, if an asker describes the question to an extremely negative state, the audience may regard it vital and be curious on the solution. Thus, I expect:

H2: Sentiment extremity has a positive relationship with the askers' profit.

4.4 Methodology

4.4.1 Research Setting

The context of this study is the Weibo Q&A. Weibo Q&A is affiliated to Weibo, the Chinese version of Twitter, and released in December 2016. Only Weibo V accounts (SocialSEO 2019), referring to verified members who can use paid advertising functions and customize the appearance of their profile pages, can apply for the service of answering paid questions. Verified answerers set the flat price of answering one question[10]. On the answerer's profile page, there is an entry point from which askers enter into stating question content and checkout page. Once the answerer responds to the question, the paid Q&A will be automatically published on the answerer's homepage with an inserted link to the answer purchase and viewing page. The paid Q&A resembles a typical Twitter message with which all users can interact, such as liking, commenting, and sharing. The only difference is that viewers have to pay RMB 1 for reading the hidden answer. Weibo Q&A is a catchall Q&A community for a variety of topics, including healthcare, investment, celebrity gossip, social issues, music, history, etc. Figure 4.2 shows an example of a paid Q&A. The answerer obtains the question answering fee and evenly shares the viewership profit with the asker. The answer will be free for all platform users to read after three months from the date of the publication.

[10] More detail about answerer guide can be found in https://www.weibo.com/ttarticle/p/show?id=2309404080081784966280&mod=zwenzhang

Translation

1. Answerer Name: 褚明宇

2. Answering time: 26th Feb, 17:50

3. Tweet content: I answered @asker 's question, the price is ¥2198.00. Everyone come and view the answer with RMB 1~

4. Question content: Could you make the matter of lovelorn clear for me......

5. Other info: 3431 people viewed the answer and 137 people forwarded, 99 people comment, and 172 people liked the Q&A

Figure 4.2 Screenshot And Translation of An Actual Q&A Post for Study 2

4.4.2 Data Collection and Operationalization

A Python 3.7-based scrapy helps complete the data collection. It crawled newly published paid Q&As every day and tracked their dynamic updates since 1st March 2019. The sampling frame in this study consisted of 9,223 questions, which were answered between March and August 2019 and had survived for at least three months on the platform. For every sample observation *i*, I collected data for variables in Table 4.2 and stored them on a local database for future analysis.

This study leveraged the Linguistic Inquiry and Word Count (LIWC) software to measure two constructs, question informativeness and sentiment extremity. LIWC is a text analysis software developed by Pennebaker et al. (2001). Psychology, management, and marketing scholars have frequently employed it to extract psychological and structural components of text samples (e.g., Boyd and Pennebaker 2015; Tausczik and Pennebaker 2010). Recently, this tool is increasingly popular for article coding and text analysis in the IS discipline (e.g., Huang et al. 2017; Huang et al. 2019; Yin et al. 2014).

Table 4.2 Summary of Collected Data for Study 2

Variable	Description	Source
$Price_i$	The asking fee that the question asker pay for $Q\&A_i$	Weibo Q&A
$Viewership_i$	The total number of users who have paid RMB 1 for viewing the answer of the $Q\&A_i$ till the last day of payment required.	Weibo Q&A
Ask_profit_i	The net profit ($Viewership_i$ minus $Price_i$) that the asker obtain from $Q\&A_i$	Computed
$Q\&A_i$	The question content of the $Q\&A_i$	Weibo Q&A
$Infor_i$	Question informativeness of the $Q\&A_i$	Computed
$Sent\_extr_i$	Sentiment extremity of the $Q\&A_i$	Computed
Ans_fans_i	The number of followers of the answerer who published the $Q\&A_i$ on Weibo on the answering date	Weibo Q&A
Ans_level_i	The membership level of the answerer who published the $Q\&A_i$ on Weibo on the answering date.	Weibo Q&A
Ans_posts_i	The number of postings of the answerer who published the $Q\&A_i$ on Weibo on the answering date.	Weibo Q&A
$Ans\_follows_i$	The number of accounts followed by the answerer who published the $Q\&A_i$ on Weibo on the answering date.	Weibo Q&A
Ask_fans_i	The number of followers of the asker who proposed the question of the $Q\&A_i$ on Weibo on the answering date	Weibo Q&A
Ask_posts_i	The number of postings of the asker, who proposes the question of the $Q\&A_i$, on the answering date.	Weibo Q&A
$Ask\_follows_i$	The number of accounts followed by the asker, who proposed the question of the $Q\&A_i$, on the answering date.	Weibo Q&A
$Topic_i$	The question topic of the $Q\&A_i$, including healthcare, finance, social focus, entertainment, parenting, travel and photography, law, fashion and beauty, history, and other topics. All Q&As are classified into 25 subjects.	Manually classified

In this case, this research used the simplified Chinese LIWC2015 dictionary (Huang et al. 2012) to compute the linguistic measures for the question content of each Q&A. LIWC reads and analyzes words contained in texts. Unlike English sentences, Chinese sentences consist of continuous characters. Thus, I need to segment each question content into dictionary words[11] before the analysis. Jieba [12] is the most widely used Python toolset for Chinese text

[11] If there are English words in the question content, one English word will be extracted as one word.
[12] https://pypi.org/project/jieba/

segmentation. It can identify newly-coined words and support to load user-defined dictionaries, which can improve segmentation accuracy. I first used python to segment 3,000 samples of question content into "words" by importing the jieba library and manually checked the segmentation results. Then, I added those unsuccessfully grouped "words" into a user-defined dictionary and loaded the user-defined dictionary when segmenting our full-sample (9,223) question content. After that, I imported the segmented question content into the LIWC software for text analysis. The text analysis output reports a comprehensive list of scales (cf. Pennebaker et al. 2015) for each question content.

Specifically, I operationalized *question informativeness* with two scales generated from the output: word count (*Infor_wc*) and cognitive processes (*Infor_cog*). Word count indicates the text length of the question content. The score of cognitive processes is calculated with the extent to which the question content contains cognitive words, such as because, know, ought, and effect. Those cognitive words demonstrate that askers may have made efforts to address problems and attempt to describe them in a logical way (Huang et al. 2017; O'Neill 2002; Pennebaker and Francis 1996). Thus, the two measures can together reflect the informativeness level of the question content. For instance, advertising literature demonstrates that the advertisement length positively impacts customers' attention through disclosing information and decreasing uncertainty (Franke et al. 2004; Tang et al. 2012). Cognitive process theory suggests that people's cognitive processes in writing guide their selection and decision process and helps clarify goals (Flower and Hayes 1981).

Second, I measured the *sentiment extremity* (*sent_extr*) by averaging the net negative sentiment scores (Huang et al. 2019). LIWC results report the positive and negative valence for each question content. Thus, I calculate the net negative sentiment scores by subtracting the positive sentiment score ("*posemo*" in LIWC) from the negative sentiment score ("*negemo*" in LIWC), that is, *sent_extr* = *negemo* - *posemo*.

We also included control variables that may affect the probability of an asker gaining a profit on one Q&A. They are the number of postings the answerer and asker publish (*Ans_posts*, *Ask_posts*), the number of accounts the answerer and asker follows (*Ans_follows*, *Ask_follows*), the number of followers the answerer has (*Ans_fans*, *Ask_fans*), the answerer's membership level (*Ans_level*), and the topic of the Q&A (*Topic*) on Weibo platform. The descriptive statistics and correlation values are shown in Tables 4.3 and 4.4, respectively.

Table 4.3 Variable Description for Study 2

Variables	Mean	SD	Min	Max
Ask_profit	-73.42	255.68	-2215.47	5169.4
Infor_wc	25.31	32.79	0	585
Infor_cog	14.81	10.77	0	100
Sent_extr	-1.13	7.60	-100	100
Ans_fans	1071229	1954600	0	1.64e+07
Ans_level	4.81	2.32	0	7
Ans_posts	28556.03	33675.85	0	764898
Ans_follows	1152.05	1829.70	0	20000
Ask_fans	15499.43	286964	0	1.64e+07
Ask_posts	1734.03	5069.42	0	181439
Ask_follows	241.46	467.20	0	7947
Topic	11.10	6.69	1	25
Notes: since the space limitation, I cannot display each of 25 topics as one variable, I coded them from 1 across 25 in sequence.				

Table 4.4 Variable Correlation for Study 2

	1	2	3	4	5	6	7	8	9	10	11
1. Ask_profit	1										
2. Infor_wc	.04	1									
3. Infor_cog	.04	.02	1								
4. Sent_extr	.04	.06	.10	1							
5. Ans_fans	-.22	.05	.05	.02	1						
6. Ans_level	-.02	.08	.09	-.04	.36	1					
7. Ans_posts	-.13	.00	.05	-.01	.5	.34	1				
8. Ans_follows	.06	.02	.04	.01	-.02	.20	.10	1			
9. Ask_fans	-.01	-.01	.00	.00	.00	.01	.01	-.00	1		
10. Ask_posts	-.07	-.06	.02	-.03	.07	.12	.09	.03	.25	1	
11. Ask_follows	-.02	-.06	.02	.00	.07	.12	.03	.03	.10	.46	1
Notes: since the space limitation, I cannot display the correlation coefficients of each topic with other variables.											

4.4.3 Model Specification

We tested the proposed hypotheses with a polynomial regression model with the asker's profit as the dependent variable using hierarchical analysis (Equation (1). Before I proceeded with the hypothesis testing, I performed robustness checks for the model specification. I conducted a link test to check whether quadratic terms are indeed the correct functional form or not in our model. Link test (Pregibon 1980; Tukey 1949) is one type of model specification error test, suggesting the fitness of a hypothesized model. I ran the link test for models with and without quadratic terms (control variables were not included in the link test). The result for the former model indicates a model specification error, but the latter model fits data well.

Furthermore, I tested the complementarity between three independent variables: infor_wc, infor_cog, and sent_extr. Two methods help us with this robustness check. First, the correlation coefficients (see Table 3.4) between the three variables range from 0.02 to 0.1, indicating that there is almost no complementarity between each two of them (Cantão et al. 2017). Second, I conducted a joint significance test for the three independent variables. The result indicates that they are jointly significantly different from zero ($F(3, 9219) = 12.87$, p-value < 0.000). Thus, our estimation equation is as follows:

$$\begin{aligned} Ask\_profit_i = {} & \alpha_0 + \beta_1{*}Infor\_wc_i + \beta_2{*}Infor\_wc_i^2 + \\ & \beta_3{*}Infor\_cog_i + \beta_4{*}Infor\_cog_i^2 + \beta_5{*}\ Sent\_extr_i + \\ & \beta_6{*}Ans\_fans_i + \beta_7{*}Ans\_level_i + \beta_8{*}Ans\_posts_i + \\ & \beta_9{*}Ans\_follows_i + \beta_{10}{*}Ask\_fans_i + \beta_{11}{*}Ask\_posts_i \\ & + \beta_{12}{*}\ Ask\_follows_i + B_{13\sim37}{*}Dummy\_topic_i \end{aligned} \tag{1}$$

4.5 Analysis and Results

4.5.1 Hypothesis Testing

We estimated a polynomial regression model. In assessing the regression model, I iteratively added variables of interest to the model in the order of our hypotheses. Table 4.5 shows the data analysis result. Column 1 of Table 4.5 shows the results of the control variables. The significance of coefficients for the linear relationships between informativeness, and sentiment extremity and askers' profit are similar in Column 2 and 3. This suggests our results are robust across estimation methods. Then, sentiment extremity has a positive influence on askers' profit ($\beta_5 = 0.033$, $p<0.000$), supporting H2. Results shown in Column 3 show that both *word count* and *cognitive processes* have a significant negative quadratic relationship with askers' profit ($\beta_2 = -0.004$, $p<0.05$; $\beta_4 = -0.014$, $p<0.01$). Thus, H1 is supported.

Table 4.5 Data Analysis Results for Study 2

Independent Variables	DV = Ask_profit_i		
	1	2	3
$Infor\_wc_i$		0.021(0.010)*	0.040(0.015)**
$Infor\_cog_i$		0.041(0.010)***	0.057(0.011)***
$Sent\_extr_i$		0.032(0.010)***	0.033(0.010)***
$Infor\_phra_i{}^2$			-0.004(0.002)*
$Infor\_cog_i{}^2$			-0.014(0.004)**
Ans_fans_i	-0.285(0.012)***	-0.287(0.012)***	-0.288(0.012)***
Ans_level_i	0.021(0.013)	0.020(0.013)	0.018(0.013)
Ans_posts_i	-0.115(0.013)***	-0.114(0.013)***	-0.114(0.013)***
$Ans\_follows_i$	-0.038(0.010)***	0.037(0.010)***	0.036(0.010)***
Ask_fans_i	0.009(0.010)	0.008(0.010)	0.008(0.010)
Ask_posts_i	-0.066(0.011)***	-0.065(0.011)***	-0.064(0.011)***
$Ask\_follows_i$	-0.002(0.011)	-0.001(0.011)	0.001(0.011)
R^2	0.179	0.183	0.184
Number of observations	9223		

Significance level: $^{+}p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$.

[a] Variables are mean-centered.

[b] I ran each model with including the topic variable as dummy variables. But, I do not display them here because of space limitations.

4.5.2 Robustness Check

We tested the robustness of our results in the way of replacing independent variables with alternative constructs. Table 4.6 is a side-by-side comparison list, displaying alternative variables for each independent variable from the estimation model. As seen in Table 4.6, there are five indexes for explaining the cognitive process of the question description, which are specific and subordinative cognitions. As for the sentiment extremity, the peripheral emotions (positive and negative) are together employed to check the consistent effect. The estimation model for robustness checks is shown as equation (2). Results in Table 4.7 suggest that findings are robust to the different measures of the dependent variables.

$$\begin{aligned}Ask\_profit_i = {} & \alpha_0 + \beta_1{*}Text\_len_i + \beta_2{*}Text\_len_i^2 + \beta_3{*}Cog\_cause_i + \beta_4{*}Cog\_cause_i^2 \\ & + \beta_5{*}Cog\_insight_i + \beta_6{*}Cog\_insight_i^2 + \beta_7{*}Cog\_discrep_i + \\ & \beta_8{*}Cog\_discrep_i^2 + \beta_9{*}Cog\_differ_i + \beta_{10}{*}Cog\_differ_i^2 + \beta_{11}{*}Posemo_i + \\ & \beta_{12}{*}Negemo_i + \beta_{13}{*}Ans\_fans_i + \beta_{14}{*}Ans\_level_i + \beta_{15}{*}Ans\_posts_i + \\ & \beta_{16}{*}Ans\_follows_i + \beta_{17}{*}Ask\_fans_i + \beta_{18}{*}Ask\_posts_i + \beta_{19}{*}Ask\_follows_i \\ & + B_{20\sim44}{*}Dummy\_topic_i \qquad (2)\end{aligned}$$

Table 4.6 Alternative Variables Description for Study 2

Independent Variables	Alternative Variables	Description	Mean	SD	Min	Max
Infor_wc	Text_len	The number of Chinese character in the question content	64.61	93.10	1	1120
Infor_cog	Cog_tentat	The extent to which that question content displays an asker's tentative cognition—relevant words such as *maybe*, *perhaps*.	3.95	5.78	0	100
	Cog_cause	The extent to which that question content displays the asker's causal cognition—relevant words such as *because*, *effect*.	3.33	5.42	0	50
	Cog_certain	The extent to which that question content displays the asker's certain cognition—relevant words such as *always*, *never*.	1.39	3.15	0	33.33
	Cog_discrep	The extent to which that question content displays the asker's discrepant cognition—relevant words such as *should*, *would*.	3.26	4.92	0	50
	Cog_differ	The extent to which that question content displays the asker's differentiated cognition—relevant words such as *hasn't*, *but*.	1.73	3.45	0	66.67
Sent_extr	Posemo	Positive emotions reflected in the question content	3.44	5.44	0	100
	Negemo	Negative emotions reflected in the question content	2.31	4.97	0	100
[a] The value for all alternative variables is from LIWC output.						

Table 4.7 Robustness Check for Study 2

Independent Variables	DV = Ask_profit$_i$	Results Consistency
Text_len$_i$	0.062 (0.0176)***	Yes
Text_len$_i^2$	-0.011 (0.003)***	
Cog_tentat$_i$	0.007 (0.013)	No
Cog_tentat$_i^2$	-0.001 (0.003)	
Cog_cause$_i$	0.063 (0.015)***	Yes
Cog_cause$_i^2$	-0.012 (0.005)**	
Cog_certain$_i$	0.014 (0.017)	No
Cog_certain$_i^2$	-0.004 (0.004)	
Cog_discrep$_i$	0.031 (0.015)*	Yes
Cog_discrep$_i^2$	-0.011 (0.005)*	
Cog_differ$_i$	0.046 (0.013)***	Yes
Cog_differ$_i^2$	-0.008 (0.002)***	
Posemo$_i$	-0.025 (0.010)**	Yes
Negemo$_i$	0.019 (0.010)*	
R^2	0.191	
Number of observations	9223	
Significance level: $^+p < 0.1$; $*p < 0.05$; $**p < 0.01$; $***p < 0.001$. [a] Variables are mean-centered. Notes: control variables are included in estimation but not be shown.		

4.6 Discussion and Implications

Creating a profitable question is meaningful for question askers to fulfill financial needs (Hsieh et al. 2010). It is also crucial for a paid Q&A platform to be viable and reap a dynamic economy in the paid content market. Prior studies have affirmed that the financial revenue has a significant positive effect on askers' participation (Hsieh et al. 2010; Zhao et al. 2020). A few paid Q&A studies have explored factors influencing answer viewership, which is strongly associated with the asker's profit. For example, Yang and Ye (2019) found that answerer-relevant metrics, such as the number of answerer's followers and postings, and the answerer's membership level, have significant impacts. However, the research question of what and how question content, framed by the asker, can directly influence askers' financial gain remains unclear.

Grounded in social presence theory (Short et al. 1976), I identified two features, question informativeness and sentiment extremity, exemplifying the perception of social presence to the question content. I argued that question informativeness and sentiment extremity could improve askers' profit through arousing prospective viewers' cognitive and mental processes, respectively. Furthermore, the current study delved into the effects of question informativeness and sentiment extremity. With a comprehensive elaboration on how askers' question framing impacts their financial gains, I proposed a more nuanced model. I hypothesized that question informativeness has a negative quadratic relationship, and sentiment extremity has a positive relationship with askers' profit. The model was tested using both originally objective data from Weibo Q&A, and coded data based on textual content with the help of LIWC. Polynomial regression analysis verified our expectations.

4.6.1 Research Implications

Theoretically, our study contributes to the existing literature in several significant ways. First, this study fills an important gap in the Q&A literature by being the first to investigate the content characteristics of the question formally. Q&A platforms have received increasing attention from scholars (Zhang et al. 2019a). Prior research in this area predominantly focused on answerers' contribution behaviors (Fang and Zhang 2019; Jin et al. 2015; Lou et al. 2013), answer quality or popularity (Kim and Oh 2009; Zhang et al. 2019a), and askers' participation motivations (Khansa et al. 2015; Zhao et al. 2020). There are relatively few empirical studies investigating what popular Q&As look like (Yang and Ye 2019), especially from the question content perspective. Thus, this study extends Q&A research, and suggests that question content features would impact answer consumption.

Second, this work offers a new perspective to examine factors influencing digital content monetization, i.e., the perspective of askers' profit. Zhao et al. (2020) found that financial gain motivates askers to propose paid questions. Moreover, past studies have substantially examined the impacts of linguistic characteristics of digital content on users' social engagement, such as sharing (Berger and Milkman 2012; Stieglitz and Dang-Xuan 2013), liking (Lee et al. 2018) and commenting activities (Lee et al. 2018; Yin et al. 2014). However, users' payment behavior on paid content platforms (e.g., paid Q&A) is a more powerful measurement for content quality and popularity. Specifically, in terms of the asker's cost in proposing a question, I operationalized the premium value of a Q&A by calculating the question profit, which is the responsible asker's net revenue from the answer viewership.

Third, this research extends the existing literature on the social presence theory. Social presence was initially used to describe to what extent a communication medium is perceived as an intimate and immediate by interactive users (Lombard and Ditton 1997; Short et al. 1976). IS scholars have successfully employed this theory to understand how communication media changes Internet users' performance, such as group cohesion (Yoo and Alavi 2001), group polarization (Sia et al. 2002), and the majority influence in a virtual group (Zhang et al. 2007a). However, it remains unclear whether the concept of social presence is applicable for illuminating the impacts of virtual interaction content on people's awareness and behaviors. The current study is an attempt to fix this gap by drawing upon social presence theory to elucidate the pattern of social interaction between the question content and prospective viewers.

Furthermore, most research on social presence theory was implemented in the laboratory setting (e.g., Harrison 2018; Qiu and Benbasat 2009) and with survey data (e.g., Brown et al. 2010). Our findings serve as an empirical validation of the features which can exemplify social presence by testing their impacts in the real world. Thus, it further adds to the social presence literature by applying it to the context of Q&A, which is an unexplored context.

Fourth, this paper provides robust evidence of curvilinear relationships between financial gain and content features, question informativeness and sentiment extremity. This suggests that the impacts of informativeness and sentiment extremity on Internet users are complicated. For example, beyond linear relationships examined in previous studies (e.g., Lee et al. 2018; Pavlou et al. 2007), this study found an inverted U-shaped relationship between question informativeness and financial gain. This finding indicates that it is not always profitable for askers to describe their problems in detail. These findings and the underlying theorization help us understand the saturation effects on an asker's profit.

4.6.2 Practical Implications

Practitioners may also benefit from the results of this study. First, to make a profit on paid Q&A sites, askers can pay more attention to frame their question content. From this study, if askers want to gain more profit from paid Q&A, they should uncover sufficient information in their questions and also leave some imagination space for prospective viewers. Besides, properly using some emotional words and exhibiting their sentiment in the question descriptions are advantaged for their profit.

Second, answerers can adjust their question selection strategies based on attributes examined in this study. With this study, answerers can make a better decision on question selection when confronting many questions remaining to be answered. They may give priority to responding to those questions which are well-framed. Although this study mainly examined the impacts of content features on askers' profit, it exhibits answer viewers' tastes to the question content. Attracting viewers will also increase the answerers' financial gain.

Third, this study provides significant insights into paid Q&A platforms. On the one hand, the platform should offer askers and answerers some functions to frame question content and choose questions. For example, since the sentiment extremity has a positive effect on the asker's profit, it will be helpful to provide a sentiment evaluation plugin so that askers can know the emotional inclinations of their question content. This function will also be useful for answerers. And, the platform may consider limiting the number of words of each question in case of askers typing into too long text. Besides, the platform can also demonstrate some examples of well-framed questions and offer some training or briefings to askers before they ask. On the other hand, the platform can improve its page rank mechanism by calculating the content features into the recommendation algorithm. In particular, the recommendation model should give proper weights to negative emotion, text length, and cognitive process.

4.6.3 Limitations and Future Research

Future research can explore more linguistic characteristics of question content. IS research has attempted to draw upon advertising and communication literature to understand Internet users' interaction with digital content (e.g., Kim et al. 2016; Weathers et al. 2015). However, there is still a great research gap in this area. Second, the pricing strategy in paid Q&A sites is still unknown, which may have a significant influence on both askers and answerers' financial gains. Third, this study is carried out in a specific profit-share scheme (see Figure 1.1). Future research may examine our model in different sharing schemes and investigate how askers and answerers react differently to the various profit-share scheme.

4.7 Conclusion

This research document through an empirical study on paid Q&A that content features of the question description can impact the question asker's profit on one Q&A. Overarched by social presence theory, this study identifies two important features exemplifying the social presence perception of the question content, which are question informativeness and sentiment extremity. I then employed a polynomial regression model to test their impacts on askers' profit with the data from Weibo Q&A. Our analysis results showed that sentiment extremity has a significant positive relationship with an asker's profit from one paid Q&A. Notably, this study found an inverted U-shaped relationship between question informativeness and askers' profit.

CHAPTER 5 STUDY 3: UNDERSTANDING DIFFERENT COGNITIVE LEVELS OF SOCIAL ENGAGEMENT: EVIDENCE FROM PAID Q&A

5.1 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 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, answerers are influencers who can produce quality content and have already attracted a great number of followers. Users on social media can pay the price set by the answerer 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 in 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, I examine how users respond to ambient factors to implement the *like* and *comment* functions differently in the paid Q&A context.

This study begins by identifying salient factors that might influence social engagement. Past research on social media found that the content creator (e.g, answerer) and consumer's (e.g., answer viewer) performance significantly impact user behaviors (Goh et al. 2013). On social media, answerers' 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). This study conceptualizes that an answerer's follower volume capture the social media popularity, representing the reputation and status on social media; while conceptualizes that free post volume capture the voluntary contributions, representing the availability of free content. The availability of free content may crowd out audiences' needs of paid content. 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, I expect it interacts with the answerer 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 the 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, this study draws 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. In this study, it is termed as low-cognitive social engagement. In contrast, users *commenting* on some content intend to express opinions and emotions with reasons. It is a systematic response requiring more cognitive efforts. It is termed as 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.

This study 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 answerer's social media popularity and voluntary contributions 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 answerer's social media popularity on users' social engagement but weakens the negative impact of an answerer's voluntary contributions. Third, the interplay impacts described before are significantly greater for high-cognitive social engagement than for low-cognitive social engagement. The 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, I 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. I then describe the research context and report the details of our data, followed by econometric models and corresponding estimation results. Finally, I conclude a discussion of the implications of the findings to research and practice.

5.2 Theoretical Background and Hypotheses

5.2.1 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 catalyzes 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, answerers 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 answerer'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 social media popularity and voluntary contributions) 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 answerer characteristics (i.e., social media popularity and voluntary contributions) and the Q&A's economic feature (i.e., viewership revenue) in users' social engagement. Thus, I hypothesize

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

H2: An answerer's voluntary contributions has an interaction effect with the Q&A's viewership revenue on users' (a) 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.

5.2.2 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, I 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, I expect the aforementioned salient factors to be more influential for low- than high-cognitive social engagement:

H3: An answerer's (a) social media popularity, and (b) voluntary contributions 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.

5.2.3 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 .

Uses and gratification theory addresses how users attend to available mediums that satisfy their needs including information, entertainment, and social interaction needs (Ko et al. 2005; Li et al. 2018). It is one of the first frameworks that recognize users' active instead of passive attendance (Dolan et al. 2016; Ku et al. 2013). While this theory has been largely applied to adopt various types of media (e.g., television, electronic bulletins, and social media), this study considers the marketing measures (e.g., answerer's social media popularity and voluntary contributions, and answer's viewership) of social media as mediums that may influence users' social engagement by satisfying their gratifications within the target content (Dolan et al. 2016; Smock et al. 2011; Swanson 1987), such as informational and social gratifications in my context.

Paid Q&A is based on social media, in which user interactions with the answer or answerer depends on their gratification needs. Answerers are influential users in social media. Audiences would prefer to consume and interact with the content generated by more popular and influential answerers (Dewan et al. 2017), which may satisfy their social gratifications. Further, answers that have been consumed by a great number of users create a herding effect on other audiences (Li and Wu 2018). Besides, the paid viewership of answers also indicates the quality and interest of the answer, satisfying audiences' information gratifications and augmenting their social needs. Thus, in this study, the effects of answerers and answer's characteristics on users' social engagement depend on the needs of gratifications from these characteristics.

Integrating the uses and gratification theory with dual-process theory, I 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 answerer 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, I expect

H5a: The interaction effect between an answerer's social media popularity 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 answerer's voluntary contributions and the Q&A's viewership revenue is smaller on low-cognitive social engagement than on high-cognitive social engagement.

5.3 Methodology

5.3.1 Research Setting and Data

I 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 answerer'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 answerer, and the real-time viewership of the answer to the question. Figure 5.1 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 5.1 Screenshot And Translation of An Actual Paid Q&A for Study 3

I 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 4.1). The collected data set consists of the answerer and asker's profile data, as well as Q&A relevant data. I 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. I 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, I 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.

5.3.2 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 $Comment_{it}$. The key independent variables are answerer characteristics and the paid Q&A's economic characteristic. I operationalized social media popularity and voluntary contributions 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.

I also included several control variables. First, answerers' 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 answerer 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 answerer, 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 ($Afollower_{it}$), following volume ($Afollowing_{it}$), 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.

I created dummy variables for categorical variables (see Tables A2-1 across A2-6 in Appendix 2). The descriptive information for continuous variables is listed in Table 5.1, and the correlation values are shown in Table 5.2. Since the correlation coefficients among *Like*, *Comment*, and *share* are extremely high, I do not include the other two as control variables when conducting estimations.

Table 5.1 Variable Description and Statistics for Study 3

Variables	Mean	SD	Min	Max	Observations
Like	24.15	175.36	0	4306	12911
Comment	9.54	51.19	0	1286	12911
Share	8.47	52.95	0	1120	12911
Follower	1347393	2060494	502	14600000	12911
Posts	33114.9	35140.41	52	190950	12911
Viewership	213.08	596.46	0	16372	12911
Following	1200.79	1640.77	0	11409	12911
Afollower	31094.38	346377.1	0	8374264	12911
Afollowing	1808.8	3600.12	0	5113	12911
Aposts	328.02	529.28	0	7221	12911
Price	143.41	462.75	0	10000	12911

Table 5.2 Correlations for Study 3

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

5.3.3 Model Estimation

I 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 I have time-invariant variables (e.g., price, answering time, answerer gender, question topic, etc.) in estimation models, I estimated random effects panel models (REPM) of our dependent variables (Bell and Jones 2015). Given the data skewness, I 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. I estimate the following panel data model:

$$\begin{aligned} Log\left(Like_{i,t}+1\right) &= \beta_1\, log\left(Followers_{i,t}+1\right)+\beta_2 \log\left(Post_{i,t}+1\right)+\beta_3 \log\left(Viewership_{i,t}\right) \\ &+ \beta_4 \log\left(Follower_{i,t}+1\right) * \log\left(Viewership_{i,t}+1\right)+\beta_5 \log\left(Post_{i,t}+1\right) \\ &* \log\left(Viewership_{i,t}+1\right)+\beta_6 Controls_{i,t} \\ &+ \mathcal{E}_i \qquad (1) \end{aligned}$$

$$\begin{aligned} Log\left(Comment_{i,t}+1\right) &= \beta_1\, log\left(Followers_{i,t}+1\right)+\beta_2 \log\left(Post_{i,t}+1\right)+\beta_3 \log\left(Viewership_{i,t}\right) \\ &+ \beta_4 \log\left(Follower_{i,t}+1\right) * \log\left(Viewership_{i,t}+1\right)+\beta_5 \log\left(Post_{i,t}+1\right) \\ &* \log\left(Viewership_{i,t}+1\right)+\beta_6 Controls_{i,t} \\ &+ \mathcal{E}_i \qquad (2) \end{aligned}$$

5.4 Data Analysis and Results

5.4.1 Hypotheses Testing

I incrementally added control variables, main effect variables, and interactive effect variables in Model 1, 2, and 3. Results in Table 5.3 show the data analysis of hypotheses 1 and 2. In Table 5.3, the results of the main effects in Model a2 and b2 are largely similar to them in Model a3 and b3, accordingly. This suggests the results are robust across estimation methods.

Table 5.3 Data Analysis Result for Study 3

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.						

As shown in Model a3 and b3, viewership has significant interaction effects with both followers and posts on both like and comment. Thus, hypotheses H1a, H1b, H2a, and H2b are all supported. Then, following Keil et al. (2000), I statistically compared the corresponding regression coefficients from Model a3 and b3 of Table 5.3 and computed the T-values shown in Table 5.4. From the coefficient differences and T-values, it can be seen that all the comparison hypotheses (H3a, H3b, H4, H5a, and H5b) are supported.

Table 5.4 The Comparison of Low and High-cognitive Social Engagement for Study 3

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

5.4.2 Robustness Check

To test the robustness of our results, I have estimated our models with robust standard errors clustered by answerers. Results are shown in Table 5.5 and consistent with previous main analyses.

Table 5.5 Robustness Check for Study 3

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

5.5 Discussion

This paper sets 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 answerer and answer's characteristics on the low- and high-cognitive social engagement? There are three key sets of findings. First, I identify and examine that an answerer's social media popularity (i.e., follower volume) and the paid Q&A's viewership revenue have a positive influence on social engagement, but the answerer's voluntary contributions (i.e., free 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. 2014a) 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, I 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, I 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, I 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, this 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, this 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, this work adds to the IS literature that examines the interaction effect between financial factors and content/content creator characteristics on user behaviors.

This 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, I 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. Further, this study conceptualizes 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.

CHAPTER 6 CONCLUSION AND FUTURE DIRECTIONS

Paid Q&A integrates social media and the online Q&A system, enabling content to flow from asking a question through answering the question to viewing and interacting with the Q&A (Lou et al. 2013). It creates economic benefits from the commercialized content by charging each transaction taking place on this system, e.g., paying to ask questions and view the answer to an existing question. This new emergent business model has attracted practitioners' attention and interest from the economic perspective (Fu 2017; Jan et al. 2018b; Technode 2017).

To have a comprehensive understanding of this novel business, I carried out three studies in this thesis to explore relevant users' consumption and engagement behaviors in the paid Q&A context. In paid Q&A, it is critical to understand how to increase answerers, askers, answer viewers, and social interaction users' participation, which conduce to the viability of paid Q&A (Kuang et al. 2019). As prior literature has explored a lot about answerers and askers' motivations to seek and share knowledge (e.g., Choi and Shah 2017; Fang and Zhang 2019; Khansa et al. 2015), this thesis focused on three other types of user engagement—answer viewers' answer consumption, askers' question framing, and users' social interactions.

Study 1 investigated what factors drive answer viewers to pay for answers. It developed a research model based on the signaling theory and literature on the dual roles of price to examine the direct and interaction effects of social and economic signals on paid viewership that an answer gains. The findings indicate that an answerer's membership level and social media popularity and an answer's like, forward, and comment volume are positive signals for answer viewers to make payments. Further, it found that question price can enhance the positive effects of like and forward volume but weaken the impacts of comment volume and the answerer's social media popularity on the paid viewership.

Study 2 investigated how linguistic features of the question content framed by an asker influence the asker's profit. It developed a research model based on social presence theory and relevant literature to examine the informative and affective impacts of question content on the asker's profit. The findings suggest that the question informativeness has an inverted effect on the asker's profit, validating the informative impact. While sentiment extremity has a positive relationship with the profit, validating the affective impact.

Study 3 investigated whether users perform different types of social engagement through distinct cognitive pathways. It developed a research model based on dual-process theory and uses and gratification theory to examine how an answerer and answer's characteristics differently impact users' different social engagements. It conceptualized that liking is one type of social engagement requiring a low level of cognition, whereas commenting requiring a high level of cognition. The findings show that the answerer's follower and post volume and the answer's viewership are salient factors influencing social engagement. Further, they have a greater direct on low-cognitive social engagement, and the interaction effect between the answerer and answer's characteristic is greater on high-cognitive social engagement.

These three studies contribute to both IS literature and practice. In particular, study 1 identified quantitative variables related to the answerer, the answer, and the answer-user interactions that drive answer viewers to pay for answers. It reveals how answer viewers attend to and interpret multiple social and economic signals in the paid context. This contributes to previous Q&A and content consumption literature by providing alternative antecedents of answer purchases and demonstrating their nuanced effects in the paid context. Also, it extends the signaling theory by documenting that people may not attend to all signals equally, and the economic signal should be strong and can moderate the impacts of social signals.

Study 2 identified qualitative variables from the question content and examined their impacts on answer consumption and profit. It contributes to the social media and content consumption literature that mainly focuses on the quantitative aspects. The findings contribute to prior literature by showing the informative and affective impacts of question content on answer consumption and askers' profit. Further, it also adds to social presence theory by extending its application to study social media content.

Study 3 explored different types of social engagement and examined the differential direct and interaction impacts of the answerer and answer's characteristics on social engagement. It contributes to user engagement literature by theorizing that liking and commenting in social media are two distinct behavioral manifestations led by different cognitive pathways. It also extended the dual-process theory and uses and gratification theory by applying them into the paid Q&A context.

Overall, this thesis contributes to the IS literature by exploring various user behaviors in the paid Q&A from the economic perspective. The deep understanding of answer viewers' purchase behavior, askers' question framing, and users' social engagement will offer insight into maximizing the economic benefits of paid Q&A for answerers, askers, and the platform.

The findings of this thesis should be interpreted in terms of their limitations. First, all three studies was derived from and tested at Weibo Q&A. The findings may be generalizable to similar paid Q&A platforms, such as Fenda.com and Zhihu.com (Jan et al. 2018b; Zhao et al.

2018), as well as other revenue models based on social media. Future research can replicate our model in other types of paid content platforms and test the generalizability of our findings.

Second, analysis data was collected in China, a country with numerous unique cultural, technique, and consumption characteristics. For example, the influential role of government regulations on culture may affect individuals' online behaviors. Future research can learn from the beneficial and doable aspects of Chinese paid Q&A site and testing the generalizability of models in other countries.

Third, this thesis only considers the paid answer consumption and social engagement behaviors. Since paid Q&A is a novel revenue model, more comprehensive and in-depth understandings about other user behaviors and the revenue strategy are worthwhile to study. For example, future research may study the process of question answering, answerer and asker selections, and question pricing. Given the data constraint, this thesis cannot capture the amount of effort that answerers have put into answering, i.e., the content production cost. Future research can explore what makes answerers produce high-quality answers. In addition, the research was conducted at the Q&A level. Future research should explore this phenomenon from a platform perspective and at the answerer level.

Fourth, the data this thesis used to examine the three studies was sufficient but limited. Future research should collect more data from this site to control as many as potential factors, and then validate whether our findings still hold. Fourth, we only focused on the volume of the comments instead of their sentiment. Finally, this thesis employed archival data to test models, which may weaken the explanation of theories. Future research can adopt survey or interviews to explore mechanisms of interesting user behaviors.

APPENDIX A SCREENSHOTS OF WEIBO Q&A

Figure A1 Screenshot of Answerers' List in the Weibo Q&A Page

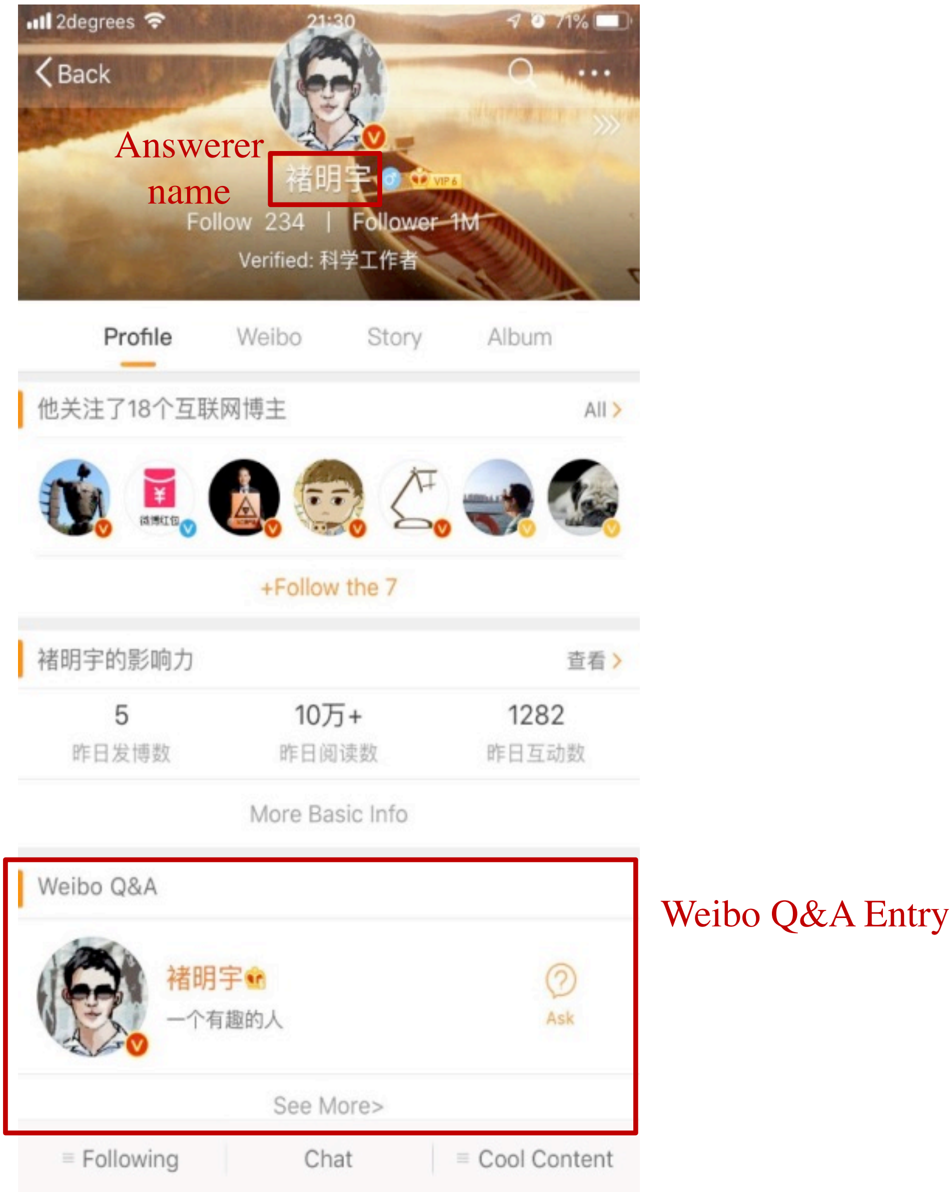

Figure A2 Screenshot of An Answerer's Homepage

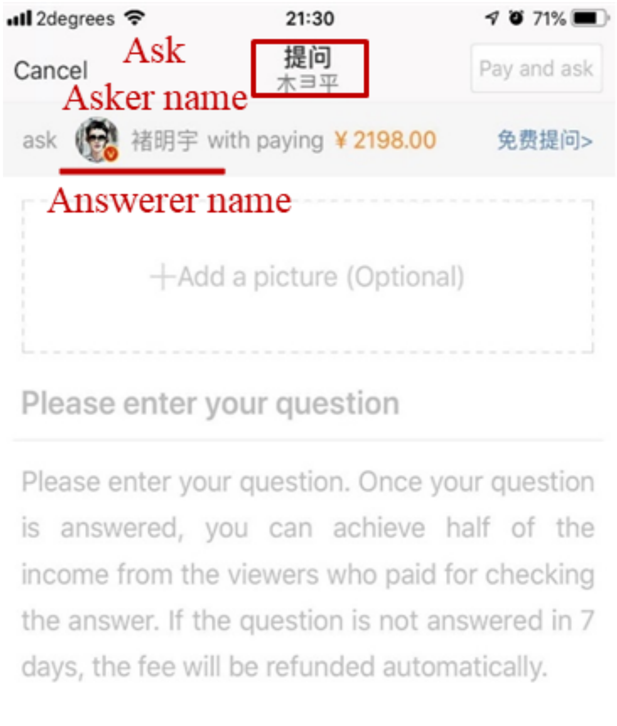

Figure A3 Screenshot of the Asking and Payment page

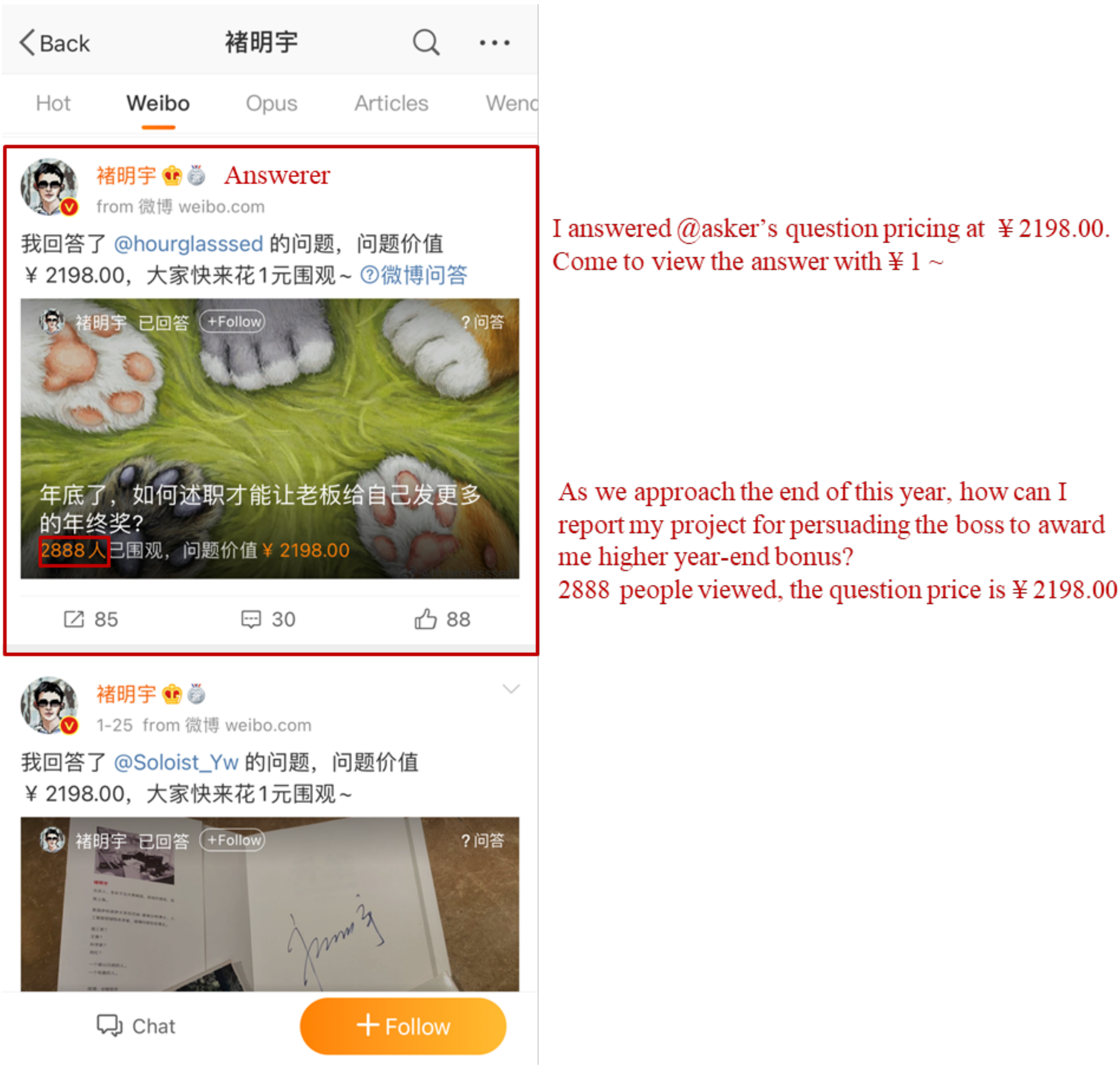

Figure A4 Screenshot of the Published Paid Q&A

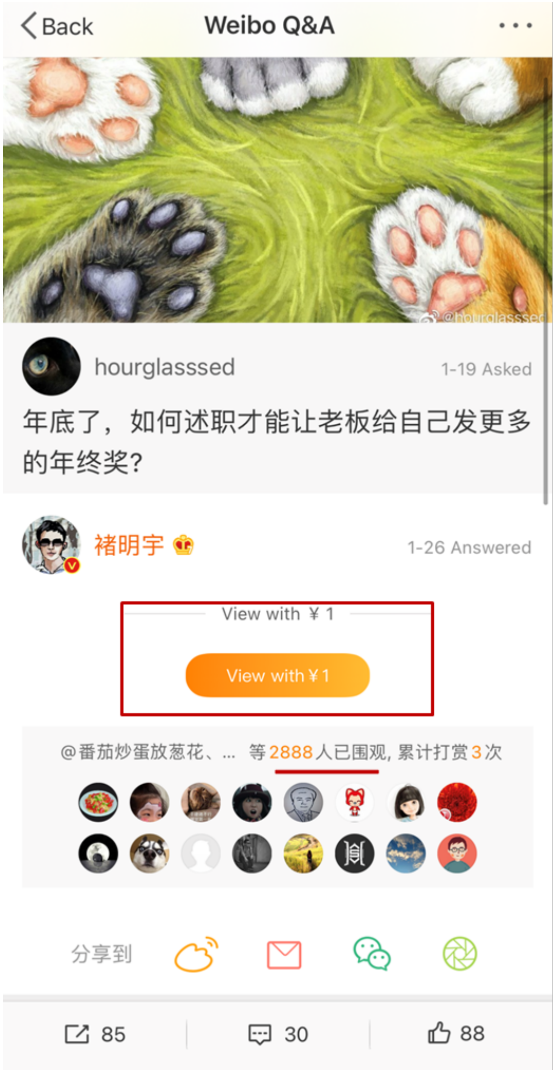

Figure A5 Screenshot of the Answer Payment Page

APPENDIX B STATISTICS OF CATEGORICAL TABLES

Table B1 Categories of Question Topic

Topic	Tag	Observations
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 (e.g., music, movie, drama, variety show, idol, cartoon)	15	1070
others	16	260

Table B2 Categories of Gender

Gender	Tag	Observations
Female	1	2478
Male	2	10403

Table B3 Categories of Gender

Agender	Tag	Observations
Female	1	2478
Male	2	10403

Table B4 Categories of Gender

Answering	Tag	Observations
Off hour	1	8401
Office hour	2	4510

Table B5 Categories of Self_employed

Self_employed	Tag	Observations
No	1	4055
Yes	2	8856

Table B6 Categories of Acertified

Acertified	Tag	Observations
No	1	12007
Yes	2	904

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