Essays on Digital Platform IT Artifacts

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A dissertation
submitted in partial fulfillment of the
requirements for the degree of

Doctor of Philosophy

University of Washington

2023

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Program Authorized to Offer Degree:

Business Administration

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Abstract

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Digital platforms implement Information Technology (IT) artifacts to improve business performance. The transformation effects of such business innovations applied in various fields such as online entertainment platforms, social media, and online communities call for further investigation. My dissertation focuses on discovering the economic values of the IT artifacts implemented by digital platforms. First, I study an online reading platform that offers a by-content purchase method and a novel in-chapter online comment function to mitigate consumer uncertainty regarding the true quality of e-books. Specifically, I seek to uncover how such intervention affects consumer purchase decisions. Utilizing a Bayesian learning framework, I unveil the consumer learning process enabled by such a by-content purchase method. I find that consumers learn the quality of books within different genres from their direct experience at different paces. Moreover, I uncover the heterogeneous signaling effects of in-consumption comments within different topics on book quality. For instance, consumers facing more comments that comprise a neutral or emotional discussion over the plot or plead the author to post new chapters would revise upward their perception of the book quality. Finally, I find that consumers approaching the end of a book or exposed to a list of chapters with few informative names tend to skip more chapters instead of reading continuously. Second, I examine the effectiveness of a potential weapon that can combat the rapid spread of public health-related misinformation on social media platforms. Specifically, I focus on Twitter's intervention that aims to suppress misinformation by helping users find accurate information.

In this study, I seek to provide a holistic view of the intervention's effectiveness by investigating its impact on true information diffusion. To this end, I employ a difference-in-differences model. Surprisingly, I find that the intervention suppresses not only the spread of false news but also true information. Further analysis reveals that true information is also suppressed because people have difficulty discerning the truthfulness of the information. Through a correlational analysis, I provide additional insights into the tweet characteristics that tend to mislead people's perceptions. Last but not least, I study individuals' engagement behaviors on an online freight driver-oriented community-based Question-and-Answer platform, with a specific focus on the difference in users' responding behaviors to urgent and non-urgent questions. To motivate users' voluntary contributions, the platform employs various IT artifacts. Through a multi-dimensional Hidden Markov Model, I provide empirical evidence on the heterogeneous effects of such motivating mechanisms and community characteristics on users' underlying motivation state transition as well as corresponding responding behaviors across urgent and non-urgent inquiries. Moreover, the analysis reveals the unintended effects of the formation of sub-groups inside the main community, alerting the online Q&A forum. While a large main community increases users' contributions, a sub-group with more members and higher exposure to unsolved questions on the platform may discourage users from contributing more responses.

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ACKNOWLEDGMENTS

Foremost, my deepest gratitude goes to my advisors: Professor Yong Tan and Professor Elina Hwang, for their continuous support and mentorship throughout my Ph.D. journey. Professor Tan has always been the best role model and mentor. Not only am I deeply inspired and encouraged by his wisdom, research enthusiasm, and humility, but also I am truly grateful for all the caring he offered me, especially during my most difficult times. With his guidance, I will always keep in mind how to be a humble and enthusiastic scholar wherever my future career goes. Professor Hwang's generous guidance and constant devotion to research have carried through my PhD journey. I heartfully appreciate her insightful ideas and support during our collaboration. Other than Professor Hwang's invaluable mentorship in research, as her teaching assistant, I am also immensely inspired by her enthusiasm, empathy, and inclusive teaching style shown in class.

I would also like to express my sincere gratitude to my committee members, Professor Stephanie Lee, Professor Ming Fan, Professor Shi Chen, and Professor Yuya Takahashi. I truly appreciate their constructive suggestions that help me refine my research study to meet a higher quality standard.

I would like to extend my gratitude to Shawna Reimers, Beau Kirkeby, Nuzulita Budhiari, Jaime Banaag, and other staff at the Foster School of Business for their generous support during my study. I couldn't go through some tough times smoothly without their help. I am also sincerely grateful to my peers and academic family with whom I share this journey.

Last but not least, I would like to deeply and heartfully thank my parents, Xiaochun Xu and Ming Liu, for their unconditional love and support throughout my Ph.D. life. Despite the 15-hour time difference between us, they would always be there whenever I need their support and encouragement. Without the strongest backing from them, I could never achieve this far.

Chapter 1

INTRODUCTION

Fueled by Web 2.0, a variety of Information Technology (IT) artifacts have been brought about to facilitate individuals and industries to adapt to today's competitive landscape. Such new technologies are widely employed on online platforms regardless of the types of services they provide. For instance, online entertainment platforms such as mobile reading and video streaming sites implement a real-time comment feature to improve users' in-consumption engagements. Social media swamped with misinformation has been designing and carrying out technology-based weapons to fight against such an "infodemic". Online communities that rely heavily on users' voluntary contributions also struggle to motivate individuals' engagement via various motivating mechanisms. Embedded with enormous potential social value and economic value, these novel IT artifacts call for further investigation by researchers and may in turn deliver future managerial implications to industries. This dissertation aims to provide a holistic view of the economic value achieved through business innovations designed and employed by digital platforms in three contexts.

In Chapter 3, I study a by-chapter purchase method and a novel in-chapter online comment feature implemented by the online reading platform. These tools enable users to form a partial understanding of the true quality of the e-books sold on the platform before making their purchase decisions. Moreover, users can purchase specific chapters instead of the whole book with limited access to the book content. Individuals' purchase decisions can thus be dynamically shaped by their reading experience and the in-chapter online comment community. Therefore, understanding individuals' decision-making processes can help unveil the mechanisms of these online reading platforms in facilitating online reading behaviors. In this study, I seek to uncover how the aforementioned interventions affect individuals' learning processes and subsequent purchase decisions. To this end, I structurally frame users' decision-making process through learning the actual quality of the books. To unveil the individual learning process enabled by the by-chapter purchase method, a Bayesian learning framework is implemented. Moreover, I investigate how the information embedded in the comment text is integrated into the individual learning process. After applying the model to a comprehensive data set from a leading online reading platform in China, I find that users learn the true e-book quality of different genres from their direct experience at different paces. Further, the analysis reveals the topic distribution patterns of the in-chapter comment content and their heterogeneous signaling effects on the book quality. For example, consumers facing more comments discussing the story plot in a neutral or emotional tone as well as those pleading for the release of new chapters would revise their perceived book quality upward. Finally, we find that users approaching the end of the book or exposed to less informative chapter names tend to skip more chapters when reading.

In Chapter 4, I investigate the effectiveness of a potential weapon to fight against the fast spread of public health-related misinformation on social media. Ranging from unproven or harmful remedies to conspiracy theories, the spread of rumors on Covid-19, measles, and vaccines has led to serious consequences such as injuries and deaths. Therefore, how to facilitate the spread of truth while suppressing falsehoods becomes an essential task. This study aims to uncover the effects of one of such potential weapons taken by social platforms to combat misinformation. In particular, I focus on a countermeasure employed by Twitter to suppress misinformation by helping users find accurate information when searching for specific health topics filled with misleading information. Through the analysis, I seek to provide a holistic view of the intervention's effectiveness by investigating its impacts on true as well as false information diffusion. To this end, I collect tweets comprising true and false information, respectively, and implement a difference-in-difference method to inspect the effect of the policy. Surprisingly, the results show that Twitter's intervention suppresses not only the cascade of false information but also true information. In a further analysis, I find that the spread of true information is also suppressed because although the countermeasure nudges people to focus on information accuracy, people have difficulty discerning the actual truthfulness of health-related content. The inspection into the diffusion of the tweets posted by authoritative accounts further verifies my findings. Due to the incapability of discerning true information, people may put more weight on the identity of accounts when deciding whether the tweet is trustworthy enough to distribute. Finally, through a correlational study, I provide potential guidance to users and the platform regarding the tweet characteristics that tend to mislead people's perceptions.

In Chapter 5, I study individuals' engagement behaviors on a community-based freight driver-oriented Question-and-Answer platform. Despite the importance of users' contribution to online communities (e.g., Quora, StackExchange, etc.), due to its public-good nature, how to keep it sustained has been bothering the platform. To continuously engage user contributions, online platforms commonly design information technology (IT) artifacts as motivating mechanisms. Meanwhile, for platforms oriented toward individuals with specific occupations such as freight drivers, questions posted by users may be highly volatile in terms of time-urgency level. Hence, users facing urgent and non-urgent questions may behave differently. In this study, I seek to explore individuals' heterogeneous responding behaviors to urgent and non-urgent questions as well as the impacts of motivating mechanisms adopted by the online community. Through a multi-dimensional Hidden Markov Model, I provide empirical evidence on the heterogeneous effects of the motivating mechanisms and community characteristics on users' underlying motivation state transition and corresponding responding behaviors across urgent and non-urgent inquiries. Moreover, I discover the unintended effects of the formation of sub-groups inside the main community, which alerts the online Q&A forum. While a large main community increases users' contributions, a sub-group with more members and higher exposure to unsolved questions on the platform may discourage users from contributing more responses.

Chapter 2
LITERATURE REVIEW

In this section, I review previous literature related to the three contexts investigated in this dissertation. Section 2.1 starts by reviewing previous studies on business models adopted by online platforms that resonate with the novel pay-by-content model, followed by introducing the literature and theory on in-consumption online comments and extant research establishing the empirical framework to model consumers' learning process when facing uncertainty in product attributes. I first summarize the theory on the formation and cascade of misinformation in Section 2.2. Then, I review previous studies examining the effectiveness of two major types of countermeasures employed by social media and bring up a research gap that remains to be explored. Section 2.3 first reviews the literature drawing on various types of users' engagement behaviors on online community-based Q&A platforms. Then, I summarize the factors that may affect users' participation on such Q&A sites based on the theoretical framework established by previous literature as well as corresponding empirical studies.

2.1 Pay-by-content and In-consumption Social Listening

2.1.1 Pay-by-Content Model

The growing trend of adopting a pay-by-content approach, as opposed to the conventional pay-by-book model on online reading platforms, resonates strongly with the established unbundling (Stremersch and Tellis 2002) and pay-per-use business models (Ladas et al. 2022). The primary advantage of this emerging business model lies in its ability to mitigate consumers' concerns arising from investing in a new product of uncertain quality. This is achieved by offering them both cost savings on individual transactions and the flexibility to allocate financial resources exclusively to content that attracts their interest. A comparison can be made with the literature's concept of unbundling, reminiscent of buying individual songs instead of a whole album, as commonly observed in the music marketing industry (Papies and van Heerde 2017). While there's an apparent similarity, a significant distinction exists between the pay-by-content and the unbundling models. Whereas unbundling is primarily about disaggregating different product combinations, pay-by-content focuses on breaking down a comprehensive product into smaller, interrelated segments (i.e., breaking a book into chapters). This distinction suggests that, unlike in unbundling, the segmentation in the pay-by-content model can lead to a connection between the divided contents, potentially influencing the consumer's decision-making process. Such a distinction, coupled with the mixed findings of the unbundling model in previous literature (Elberse 2010), raises the importance of understanding how would consumers make purchase decisions within the emerging pay-by-content business model.

Furthermore, the pay-by-content model offers readers the flexibility to selectively access specific chapters of a book based on their needs, eliminating the necessity to acquire the entire book. This adaptive payment approach resembles the pay-per-use business model, well-documented in the literature, where users pay a nominal fee per use instead of gaining permanent ownership of the product (Gilbert et al. 2014). Yet, unlike the pay-per-use model where consumers typically pay for access to the entire product for a limited duration, in our context, consumers have the freedom to read individual chapters of a digital book in sequence without any time constraints. Given the inherent linkage between the divided contents (i.e., chapters of a book), the factors driving consumer decisions in our context could differ from those in the pay-per-use model.

Finally, the emerging pay-by-content model resonates with another business strategy taken by online entertainment platforms, i.e., sampling and freemium. This approach aims to improve consumers' purchase intention by offering them free samples so that consumers can immediately experience the partial product content at no cost (Choi et al. 2019). However, previous studies have shown that the quality level of these free samples may differ from that of the original product, which can lead to consumers' dissatisfaction after purchase (Li et al. 2019). This further motivates our study, as the potentially distorted experience provided by free samples could lead to consumers ending up making unsatisfying purchases at a high cost, but the pay-by-content model allows consumers to make each purchase decision based on their most up-to-date perceived quality at a relatively low cost. The enhanced flexibility and reliability inherent in the pay-by-content model underscores its potential to alleviate consumer concerns about investing in new products with uncertain quality.

2.1.2 In-consumption Online Comments

In-consumption comments, a novel form of in-consumption data, are facilitated by the emerging real-time commenting features seen on online entertainment platforms [1]. These comments allow both platforms and researchers to monitor in-consumption consumer responses to fluctuations in a product's content (Zhang et al. 2020). Unlike other in-consumption data types, such as eye and face tracking—which remain private to the individual consumer—these real-time comments are accessible to all consumers engaging with the same content. This unique data type provides an opportunity to understand how a consumer's in-consumption reactions might influence others during their content consumption, enabling them to conduct more informed intertemporal purchase decision-making.

Such in-consumption comments resonate with online product reviews, another type of user-generated content related to consumption experience. When determining whether to adopt a new product, consumers tend to search for credible information about the attributes of the product, especially when the product possesses intangible and experiential features (Mahajan et al. 1984), such as experience goods like books, travel, and games (Nelson 1970). In contrast to possibly distorted and incomplete information provided by sellers, online reviews generated by other consumers who have already experienced the product are more user-oriented and therefore, are of a greater reference value to consumers (Wilson and Sherrell 1993). Previous literature has shown that consumers incorporate information from other consumers' experiences conveyed in online reviews (Wu et al. 2015), sometimes even more than their own experience (Zhao et al. 2013). Various features of online reviews, such as volume (Park et al. 2007), valence (Vermeulen and Seegers 2009), variance

[1]This feature is not unique to online reading platforms as in our context. It is also trendy among live-streaming websites such as TikTok and BiliBili.

(Park and Park 2013), sentiments (Hu et al. 2014), and context-specific textual features (Liu et al. 2019) have been proven to have significant impacts on consumers' purchase intentions and product sales.

Despite the resemblance, there exist distinct differences between in-consumption comments and online reviews. While online reviews tend to provide a post-consumption overview of the product as a whole, in-consumption comments capture real-time reactions and granular feedback specific to individual moments or sections of the product. Hence, these comments tend to be more concise [2] and often reflect immediate, spontaneous reactions of the consumers who post them, rather than offering a comprehensive assessment of the product's overall quality like online reviews do. How consumers perceive such implicit comments from others when making purchase decisions, however, remains under-explored. Moreover, online reviews often focus on summarizing the overall experience and may be influenced by recency bias (Sparks and Browning 2011), where the most recent experiences overshadow earlier ones. Lee et al. (2021) also found that online reviews may be posted based on incomplete consumption experience, which may mislead future consumers who haven't experienced the product themselves. These problems are alleviated with in-consumption comments, thanks to them offering consumers a continuous and immediate stream of their peer's feedback during their own consumption journey. This distinction enables a deeper understanding of how a consumer's purchase decision-making might be influenced by real-time reactions from others throughout the product.

Given the distinct characteristic of in-consumption comments—that they record consumers' immediate responses to temporal changes in a product's content—we conceptualize the consumption of such products (such as reading books) following the information-processing framework established by Lang (2000). The framework suggests that the orienting response could steer the information-encoding process of information receivers. The orienting response is an automatic physiological and behavioral response that occurs in response to stimuli, such as novel stimuli, which refers to a change in the environment (Pavlov 1927). In the context of online reading, such

[2] In our context, all of the in-chapter comments contain less than 10 words.

changes are interpreted within the context of book content, such as the story flow. The occurrence of an orienting response leads to the reader orienting their sensory receptors toward the stimuli that trigger the response (Lynn 2013), thus allocating more processing resources to encode the information embedded in the stimuli. Accordingly, we can conceptualize the consumption of the reading experience in a book as a continuous communication process, which flows from the author to readers. The author would craft a series of temporal content variations throughout the book (e.g., plot development and shifts in character behavior) with the intention of eliciting readers' orienting responses to the content. If such delivery of a narrative experience is successful, readers often react with active participation, reflected by their participatory responses and inferences (Bezdek et al. 2013). For example, readers may make mental inferences when characters make decisions (Jacovina and Gerrig 2010). Consider a moment in Tim O'Brien's short story where the main character bets $12,000 on one game of blackjack. This big decision might make some readers think, "Good for him! He's got guts." But others might feel, "That was a silly thing to do.". This active participation, captured by the in-consumption comments in our data, often indicates that readers are deeply immersed in the story, almost as though they are living through the events in the narrative themselves (Green and Brock 2000). However, in the setting of in-consumption online commenting, the comments may not solely act as a form of active participation, especially when the book's content does not sufficiently engage the readers (Berger 2014).

In our context, it's important to recognize that communication occurs not only between authors and readers, but also among the readers themselves, facilitated by in-consumption comments that are open for all to see. However, how the consumer interprets others' participatory responses to the book content remains an underexplored question. In light of this gap, we developed a model capturing the consumer's inference of the book's quality from various categories of in-consumption comments.

2.1.3 Consumer Learning Process

Facing the imperfect information provided by sellers, consumers would generate a high uncertainty of the quality of products, especially for experiential products (Kirmani and Rao 2000, Nelson 1970). Unlike the traditional discrete choice framework which assumes consumers know the product attributes perfectly, new learning models were proposed in a stream of literature that accommodate for the incomplete information faced by consumers (Meyer and Sathi 1985, Roberts and Urban 1988). Specifically, consumers would make adoption decisions based on their perceived product quality. Over time, consumers receive signals from their experience or other sources that facilitate them to obtain more product information. Using the new information, consumers would keep updating their beliefs about product quality (Ching et al. 2013). One pioneer paper applying this learning framework to practical problems is (Erdem and Keane 1996), modeling consumers' learning process from their past purchases and advertisements. The learning model has been applied to various empirical settings, such as insurance (Israel 2005), e-commerce (Zhao et al. 2013), and restaurants (Wu et al. 2015).

This paper develops a model following the stream of the learning literature. Specifically, when consumers start reading a new e-book, there is considerable uncertainty regarding the actual quality of this book. To mitigate this uncertainty, consumers engage in a learning process as they progress through earlier chapters. This learning incorporates two information streams: their own direct reading experiences and the indirect reading experiences of previous readers, as reflected in in-consumption comments. Utilizing the information, consumers revise their belief about the book's quality using Bayesian updating. Upon completing a chapter, consumers would determine which following chapter to purchase.

2.2 Misinformation and Countermeasures

2.2.1 Misinformation

Misinformation refers to false or misleading information that can arise from various sources. Although some misinformation has comparably benign origin as they come from evolving events which requires unavoidable and unintentional updating process of knowledge, many other sources of misinformation are intentional and harmful (Lewandowsky et al. 2012). Serving as a catalyst to the diffusion of both true and false information, the Internet tore down the barrier built up by traditional “gate-keeping” mechanisms (e.g., professional editors) between the access to new information and ordinary people. Especially with the development of Web 2.0, Internet users are able to actively create content on social medias such as Twitter and YouTube without being censored beforehand, which facilitates the spread of misinformation.

Despite the worrisome “infodemic” swamping the Internet, information on the Internet progressively replaces professional advice in all fields, including public health. According to a report, around 80% of adults in the US and 66% of adults in Europe seek online health advice (Taylor and Leitman 2002). Prior research and survey also suggest that young people are particularly attracted to the Internet, viewing it as a valuable source of information and advice, especially when they have sensitive or stigmatized diseases (Berger et al. 2005). Seeking the Internet for information and help, however, is risky because of the highly variable accuracy of the information. A study conducted by Ohio State University reviewed 60 health sites for information pertaining to childhood diarrhea, and found only 20% of the sites provided trustworthy information whereas 80% gave incorrect and possibly dangerous information to the general public (Pastore 2000).

As mentioned in previous section, the cascade of misinformation on social media can lead to serious social and economic consequences. The existence of popular myths in public health field is not restricted to infectious diseases like Covid-19 and measles. A recent report shows that one-third of popular cancer articles on social media such as Facebook from 2018 and 2019 contained misinformation, and the majority of them contained potential harmful information (Johnson et al. 2021). Online videos are also effective and popular means of disseminating information. Prior studies have examined videos of prostate cancer on YouTube and found that around 77% of the popular videos contained potentially biased content within the video or comments section, with a total reach of >6 million viewers (Loeb et al. 2019). The topics of misinformation ranges from conspiracy theories to various bogus treatments (Chen et al. 2018), and a study found that people with cancer who had used alternative or complementary treatments instead of conventional cancer care had a greater risk of dying than people who received conventional cancer therapy (Johnson et al. 2018).

Previous studies found that while the implant of misinformation is easy, its influence tend to be long-lasting. According to the tacit assumptions that govern the conduct of conversation in daily life, "Communicated information comes with a guarantee of relevance" (Sperber and Wilson 1986), and listeners are entitled to assume that the speaker tries to be informative, truthful, relevant, and clear (Schwarz 1994). Some prior research even suggests that in order to comprehend a statement, people must at least temporarily accept it as true (Gilbert 1991). Belief in the new information, therefore, may be a necessary condition of comprehension. Although suspension of the belief is possible, it is not favored in most situations where there is no obvious and concrete evidence that can raise a higher degree of attention or distrust of the audience at the time the information is received (Schul et al. 2008). Especially, if the topic of the information does not appeal to the audience, misinformation can easily slip in due to lack of attention and motivation to suspect the truthfulness of the information. Contrary to the easy implant of misinformation, misinformation tends to be sticky and persistent in memory (Thorson 2016). Prior literature suggests that when people encounter new information, they build a situation model based on their perceived initial information to encode the new information (Bower and Morrow 1990). Although this situation model is continuously updated to reflect up-to-date changes, it has been shown that the primary situation model that people build is well integrated in memory, and people exhibit a primacy effect, i.e., they tend to remember the first piece of information they encounter better than information presented later (Schul and Mayo 2014). Moreover, previous studies indicate that the primary situation model is reluctant to subsequent change if the change involves the invalidation of information previously believed to be accurate (Ecker et al. 2015, Rapp and Kendeou 2009) Misinformation, therefore, tends to continuously influence memory and reasoning. Even strong correction or retraction of misinformation can only create a "gap" at a superficial level instead of complete removal in the situation model, failing to eliminate continued influence effects of misinformation (Ecker et al. 2011).

2.2.2 Misinformation Countermeasures

The growing concerns of widespread public health misinformation online has impelled social media companies to develop and implement interventions to fight against the spread of falsehood

(Chou et al. 2018). A widely applied misinformation countermeasure taken by social medias, known as the censorship-based approach, is to inspect the content of individual posts and tag the falsehoods with warning flags or delete them. Facebook, for example, has deployed a range of approaches such as red-flagged warnings (Mosseri 2016), showing fact-checking articles as related articles (Smith 2017), asking for confirmation before sharing, and reducing the post's size (Clayton et al. 2020). These countermeasures are applied to misinformation that are confirmed by experts after propagated, and therefore correspond to warnings in the aftermath. Corrections of misinformation online sometimes can be successful in the short run, if the debunking message sent by the social platform to users is detailed enough to reduce misinformation persistence (Chan et al. 2017). However, corrections may fail if they are not manipulated adequately. If corrective messages directly or indirectly repeat misinformation in order to correct it, they may enhance the familiarity and perceived truthfulness of the falsehood, and exhibit a backfire effect (Nyhan et al. 2014, Garrett and Weeks 2013). Moreover, since such interventions can only be applied after the post of misinformation, an inevitable time lag between the delivery of falsehood and the correction is exerted, which may also allow the repetition of misinformation before corrections are placed, leading to inefficacy of the countermeasure (Walter and Tukachinsky 2020, Cook et al. 2015).

2.2.3 The effect of Twitter intervention on true information

Different from the censorship-based countermeasures listed above, Twitter's policy provides users with reliable sources for trustworthy information in advance, instead of alerting users after the propagation of misinformation. Such approach may generate an implicit forewarning to users of misinformation embedded in the search results that they are going to access. A recent study examines the effect of Twitter's policy on the diffusion of false articles, and the researchers find that this countermeasure efficaciously decreases the probability of a false article to be shared on Twitter and suppresses the further spread of it (Hwang and Lee 2021). Misinformation, however, is not the only type of information spread online that may be affected by social media's interventions. The impacts of Twitter's policy on information of other truthfulness such as true information remain unclear. On one hand, as mentioned in Section 2.2.1, people would build a situation model based on their initial reception of information to encode new information, and this primary situation model resists subsequent change which requires people to invalidate their previously accepted information (Cohn 2019). When users search for certain topics on Twitter, a prompt containing reliable sources is generated by the platform and is shown at the top of their search results. Therefore, if users follow the link embedded in the prompt and check the trustworthy information of the topics before moving to their search results, they may remember the true information better than the information contained in the result tweets. On this view, Twitter's policy may facilitates the cascade of true information in that users are able to access reliable information first and it may be more difficult for the information presented later to debunk their belief about the primary information that are perceived as accurate.

However, such effect may not be guaranteed. A disconnect between people's sharing tendency belief of information has been discovered in prior literature, i.e., belief in misinformation is not a necessary condition of sharing, in that the intention of people could be shifted to other aspects of the information (Pennycook et al. 2020a). As indicated by Roozenbeek et al. (2021), accuracy nudges such as asking people to evaluate the accuracy of a random piece of unrelated information may enable people to consider information accuracy before deciding whether to share, and hence may suppress their willing to share false information. Nevertheless, similar conclusion may not be applicable to true information and the researchers even found negative effect of such intervention on the sharing tendency of true information. Moreover, different from the setting of previous research, since Twitter's policy only contains links to reliable information sources instead of displaying full content of truth information or directly asking users to concentrate on information accuracy, users may not follow the links depending on their preferences, failing to access true information beforehand, and therefore directly proceed with their search results. In this situation, it is unclear whether users receive the trustworthy information embedded in the search prompt before being exposed to possible misinformation or perceive the search prompt as an accuracy nudge.

Previous studies have also proposed possible mechanisms behind the effectiveness of misinformation countermeasures. Exposure to a general warning of widespread false news may result in a decrease in people's belief in the accuracy of true and false information (Clayton et al. 2020).

Meanwhile, Pennycook et al. (2020b) conducted a lab experiment and showed that a simple intervention that serves as an accuracy reminder at the beginning of people receiving new information is more likely to nudge people to consider the accuracy of the new information when deciding whether to share it. Given this mechanism, the extent to which the intervention affects the spread of the information should reflect people's underlying belief in the accuracy of the information. However, such mechanism is still in lack of empirical inspections. In this paper, we empirically discover the underlying procedure of the effectiveness of Twitter's misinformation countermeasure, examining whether and how the policy affects the diffusion of information with different truthfulness through enabling people to turn their attention to information accuracy.

2.3 User Engagement and Influencing Factors

2.3.1 User Engagement Behaviors on Community-based Q&A Platforms

Gathering individuals across different geographic locations, online community-based Q&A platforms provide a channel for users sharing mutual interests or identities to ask questions and solve problems (Wasko and Faraj 2005). Such platforms rely heavily, sometimes even solely, on users' voluntarily generated content (Jin et al. 2015). Registered users can post questions on the forum and wait for other users with relevant knowledge to supply answers.

The efficacy and popularity of the Q&A platforms has attracted the attention of many researchers, focusing on users' information-seeking and information-retrieving behaviors (Rosenbaum and Shachaf 2010). Some prior studies explored efficient methods users can employ to identify the high-quality answer to their questions among the massive responses they might receive on the forum (Agichtein et al. 2008). Meanwhile, others aimed to discover the sources facilitating users to answer the questions posted by other users (Oh et al. 2008). In addition, some researchers seek to compare individuals' initial participation behavior and continuous engagement behaviors (Guan et al. 2018).

Despite the extensive body of prior studies on various types of users' engagement behaviors, few researchers have been focusing on the different dimensions a user's behavior may comprise.

In particular, an individual's responding behavior may vary on different types of questions. Extant literature on this trend primarily concentrates on different question types driven by the associated questioners' identity, especially the hierarchy levels Hwang et al. (2015). Pu et al. (2022) reported that the hierarchy barrier in the corporate-hosted Q&A site is hard to cross as employees are generally reluctant to respond to the questions posted by their higher-ups. Apart from the questioner's rank, the time-urgency level of the question may also be an essential attribute. In specific occupation-related communities such as a freight-driver forum or a doctor-patient medical platform, questions posted by users may be volatile respecting the urgency level (Kim and Yoon 2012). For instance, the inquiry of a driver caught up in a car accident regarding insurance would be more urgent than a general question about the traffic condition of a city. As such an urgency level potentially implies the safety condition of the questioner, users facing urgent and non-urgent questions may behave differently. To the best of our knowledge, this is the first paper to focus on examining individuals' responding behaviors across questions with different time-urgency levels.

2.3.2 Factors Affecting User Participation

One main driver of user contribution in an online community is motivation. Following previous literature, we classify motivation into three types: intrinsic, extrinsic, and internalized extrinsic motivation (Von Krogh et al. 2012). Intrinsic motivation refers to inherent reward drivers, such as altruism, joy, and self-efficacy (Ozinga 1999, Tedjamulia et al. 2005). In the context of community-based Q&A sites, for example, individuals may help others by answering their questions due to the enjoyment obtained from helping others. Extrinsic motivation, in contrast, is stimulated by external incentives including monetary rewards, career prospects, etc. (Kollock et al. 1999, Chen et al. 2022).

Meanwhile, as an integration of the aforementioned two types of motivations, internalized extrinsic motivation arises from external incentives, but is then perceived as being chosen by oneself, such that the user behavior is internally regulated in a self-determined way (Ryan et al. 2002). Common examples of internalized extrinsic motivation in online communities include reciprocity and reputation (Von Krogh et al. 2012). In the context of Q&A platforms, reciprocity proposes that users whose questions were answered by others are inclined to provide answers to others' questions (Chiu et al. 2006). Reputation refers to the user-identity enhancement achieved by peer recognition and self-image. Recognition from other community members would validate the expectation of the role played by the user in the community (Ray et al. 2014), further convincing the user regarding their identity uniqueness and encouraging their contribution (Ghosh 2005). Therefore, on Q&A sites, users may value recognition from others, such as the acceptance of their contributed answers as the solution to the questions. Other than peer verification, concerns about self-image may also drive user contribution. It has been shown that people care about how others perceive them, which motivates them to make contributions in order to build a better image in the community (Kankanhalli et al. 2005). In online communities, users with outstanding contributions (e.g., whose responses solve a widely concerned question) could be recognized by the platform through a bulletin, which may improve their self-image.

Another factor that may affect user participation in online communities is the social relationship among users (Malinen 2015). While fostering relationships between individuals is not a vital part of Q&A sites, some platforms allow their users to form smaller groups in the community according to a mutual feature, such as geographic location. The platform may also share unsolved questions directly with the small groups. However, whether and how such small groups would affect user contributions remain under-explored. On the one hand, previous studies have shown that a more inclusive group can enhance the confidence of group members in providing information(Kraut et al. 2010). A minor group with users based in the same city may imply a tightly bonded relationship among the members. Therefore, users belonging to such groups might tend to make more contributions to the community. On the other hand, the existence of group mates may incur a social loafing problem, as users are aware of the exposure of other group members to the questions and thereby may perceive their own contribution as less necessary (Karau and Williams 1993). Aiming to address this gap, our study contributes to this stream of literature through a more granular identification regarding the effects of user motivation and minor groups in online communities.

Chapter 3

LEARNING WHEN READING: EVIDENCE FROM AN ONLINE MOBILE READING PLATFORM

3.1 Introduction

The evolution of online entertainment platforms has led to the emergence of live comments, also known as in-consumption comments, which represent a dynamic form of word-of-mouth (WOM). These comments differ from the traditional WOM, which occurs post-consumption, as they are generated and viewed in real-time while the consumer is engaged with the content, which enables platforms to track and monitor consumers' real-time reactions. This new data stream has gained a growing interest from researchers in exploring its economic value (Zhang et al. 2020, Lin et al. 2021).

In-consumption comments resonate with online reviews, another form of WOM, but exhibit distinct differences. Online reviews play an important role in affecting product sales and consumer decisions. Compared with seller-provided information, they are more detailed, trustworthy, and user-oriented; hence, they facilitate consumers to find products matching their preferences and reduce the likelihood of later regretting a decision (Chen and Xie 2008, Duan et al. 2008). Researchers have shown that various features of online reviews such as volume (Chen et al. 2004) and valence Chevalier and Mayzlin (2006) have significant impacts on product sales and consumers' purchase intentions.

In contrast to the post-consumption overview of the product as a whole provided by online reviews, in-consumption comments capture consumers' real-time reactions to temporal variation in the product content. That is, these comments often reflect immediate, spontaneous reactions of consumers during consumption, rather than trying to offer a comprehensive assessment of the product's overall quality like online reviews do. Additionally, unlike online reviews which may suffer from recency bias (Sparks and Browning 2011), in-consumption comments offer a continuous and immediate stream of feedback, painting a more comprehensive picture of the consumer's journey throughout the product.

This study, among the first of its kind, aims to uncover how consumers learn the quality of a new product from in-consumption social listening, captured by these in-consumption comments. Specifically, we focus on the context of online reading platforms, which have adopted a novel in-consumption online commenting feature that enables consumers to comment on specific pieces of text within each chapter. These comments are visible to all consumers reading the same chapter. Utilizing these comments, consumers may be able to alleviate their concern rising from the difficulty in identifying the true quality of experience goods, such as e-books in our context, when making purchase decisions.

Additionally, the online reading platforms in our context adopt a new business model, known as the pay-by-content model. Different from the traditional pay-by-book model adopted by platforms like Amazon Kindle and Rakuten Kubo where consumers are required to purchase a whole book per transaction, the pay-by-content model allows consumers to buy a new book by its chapters. Specifically, consumers are enabled to read the first chapter of a book and then decide on which following chapter to buy next upon completing that chapter, even if the new selected chapter is not the consecutive one. This process then repeats with each chapter read by consumers, until they either finish the book or quit reading. Such a pay-by-content model not only reduces the cost of consumers per transaction[1] but also grants consumers high flexibility to pay only for the content they are attracted to, thus able to mitigate their concerns about investing in a new book of uncertain quality.

Under this pay-by-content model, despite being unable to ascertain the true quality of an e-book beforehand, consumers may learn the quality based on both their direct reading experience of consumed chapters and previous readers' indirect reading experience embedded in in-consumption comments. Following the Bayesian learning framework developed by Erdem and Keane (1996),

[1]Consumers pay for a chapter per transaction, which costs much less than a whole book.

we then developed a structural model to frame consumers' learning process. To capture the potentially different indirect experiences of previous readers, we utilized a combination of the Word2Vec algorithm and cluster analysis to explore the content topics of the in-chapter comments. We conceptualize the discovered topics following the in-consumption information-processing framework (Lynn 2013) and the taxonomy developed by Bezdek et al. (2013). These comments are then incorporated into our proposed model to investigate their signaling mechanisms of book quality.

We then applied the proposed model to a unique panel data set, comprising 1,166 e-books read by 4,354 consumers, obtained from one of China's most popular online reading platforms. Based on the estimated model, we further conduct a series of policy simulations. We elicit the following unique findings through our empirical analysis. First, we find evidence that consumers learn the quality of different genres of books at a different pace. The reading experience provided by gender-neutral fiction is much more stable than that provided by teen fiction. Second, our results reveal the product-signaling mechanisms of in-consumption comments across different topics. Consumers facing a high volume of comments making inferences based on current scenes, pleading for the release of new chapters, or judging the character's behavior would revise upward their perception of the book's quality. Meanwhile, a high volume of comments comprising purely happy emotional words or those depicting a desired hypothetical future scene would decrease consumers' perceived book quality. Our policy simulation findings align with the estimation results and further show that reducing the variability of comment volume would be much more efficient than increasing the comment volume in terms of improving consumers' continuous reading intention. Third, a consumer would tend to skip fewer chapters after finishing reading the current chapter if the chapter names of the focal book are more informative or if she is approaching the end of the book.

3.2 Study Context and Data

3.2.1 Study context

We collected the data for this study from one of the most popular online reading platforms in China, which has approximately 30 million monthly active users. The platform provides consumers with a mobile application launched in both primary Android and iOS app stores, enabling consumers to purchase e-books by chapter. With millions of e-books that cover a wide range of genres such as teen fiction and romantics accessible on the platform, consumers can choose from a massive collection to find the e-books that attract their interests and fit their tastes.

When a consumer enters the platform, she can first pick a book and browse the default book page exhibiting the introductory information[2]. The consumer then forms a prior expectation of the book's quality and then chooses whether to start reading the book based on her expectation. If she chooses to start reading, she will enter the first chapter. Figure 3.1 shows the default layout of a chapter page presented to consumers with an example of a chapter from a sample book. When the consumer reads a chapter, she may discover certain small numbers that appear below a sentence or at the bottom of a page, as shown in figure 3.1 (a). These numbers indicate the number of in-chapter comments on the current sentence or page. These comments are posted by other consumers who have already read the sentences or pages. If the consumer is interested in others' thoughts and feelings about a sentence or a page, she can click on the associated number. As shown in figure 3.1 (b), she will then be navigated to the built-in page that presents the detailed textual content of each in-chapter comment.

At the end of the chapter, the consumer is prompted to decide whether to purchase the next chapter. If she decides to do so, she may click on the "resume reading next chapter" button, pay for it, and be directed to the next chapter page. However, if she chooses not to read continuously at this point, she can use the "return to chapter list" button to browse the full chapter list of the book. She may then skim through the names of all chapters, acknowledge her current position in the book, and then determine which following chapter to read next. She can directly jump to that selected chapter from the chapter list. At any time point, the consumer may quit reading the whole book.

[2]The platform enables authors to serialize chapters of their books. That is, authors are allowed to keep posting new chapters of an existing book instead of posting all the chapters at first attempt.

Figure 3.1: A sample chapter page and bullet page.

(a) screenshot of a sample book chapter. The number appearing below each sentence indicates the number of in-chapter comments of this sentence; the number shown at the bottom of the page indicates the number of in-chapter comments of the current page. (b) screenshot of sample in-chapter comments' content page. The page shows text content of all the comments to the current sentence or page.

3.2.2 Data description and Preprocessing

To construct the data for this study, we randomly sampled 1,200 e-books launched on the platform before April 2019 that contain bullet-like comments. The platform then provided us with three data sets: (1) generic information about the books, including book titles, chapter prices, and genres defined by the platform; (2) data on in-chapter online comments embedded in the books, which comprises the post dates, the ID of the owners of the comments, the number of the specific chapters where the comments are posted in, and the textual content of the comments; and (3) data on the entire reading history of each consumer of each book, including the reading dates, the chapters that the consumer read, and the payment amount spent by the consumer for each chapter she reads. For model calibration, we followed the preprocessing procedure in the learning literature in handling heavy buyers (Erdem and Keane 1996). We kept only the reading history of the consumers who made more than 10 purchases and less than 50 purchases of book chapters. It is difficult to identify the underlying learning model from the noise for a reading record where the consumer made fewer purchases. Meanwhile, the computational cost to estimate the model is beyond our capacity with a reading record where the consumer made more purchases. After screening the raw data sets, we ended up with the data on 132,585 chapter purchases made by 4,354 individual consumers of 1,166 e-books.

To explore the content topic clusters of the in-chapter comments embedded in the books, we implemented a cluster analysis. Specifically, we first trained a Word2Vec model based on the corpus comprising segmented words from 1,896,819 unique comments[3] to learn the numeric word embeddings of the comments(Mikolov et al. 2013). We then applied a k-means algorithm to cluster the comments. To determine the optimal number of clusters, we implemented an Elbow method (Bholowalia and Kumar 2014) to determine the optimal number of clusters, as shown in Appendix. We then chose the number of clusters of comment topics to be five. In Figure 3.2, we visualize and summarize the comment topic clusters[4]. We use the taxonomy of participatory responses

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[3]For segmentation of comments, we used jieba, a state-of-art Chinese word segmentation algorithm: https://github.com/fxsjy/jieba

[4]The original Chinese version of the topic clusters are visualized in Figure A.7.1 in Appendix.

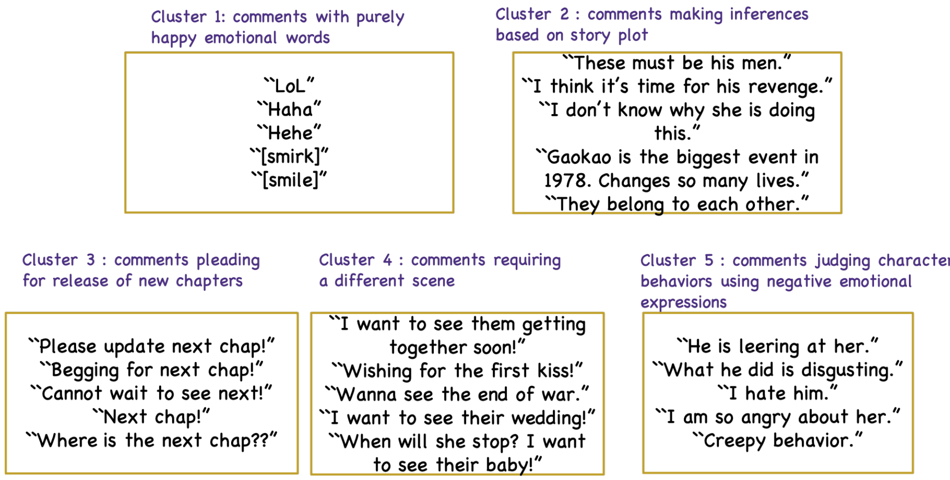

Figure 3.2: Visualization of top translated clustered in-chapter comments.

Cluster 1 comprises 80,692 comments filled with happy emotional expressions, cluster 2 comprises 1,294,929 comments making inferences based on the story plot, cluster 3 comprises 73,050 comments begging the author to post the next chapters soon, cluster 4 comprises 385,771 comments asking for a new scene, and cluster 5 comprises 62,377 comments judging the character behavior using negative emotional expressions.

and inferences established by Bezdek et al. (2013) to conceptualize the discovered topics of these in-chapter comments. Specifically, topic-1 comments would fall into the emotional participatory response category that comprises readers' responses as if the events were occurring in real life, with a major component of a sense of amusement. Topic-2 comments are categorized as inferences, which reflect readers' neutral inferences based on the current scene. These comments are more informative, in terms of adding the reader's deduction to the narrative. Showing a straightforward expectation of new chapters, topic-3 comments are unique to our context and cannot be classified based on the current taxonomy. While these comments are not elicited by a specific scene in the chapter, they reflect a strong narrative engagement of readers such that the readers are eager to know what happens next. Topic-4 comments correspond with consequence inferences and outcome-preference participatory responses. These entail the reader's predictions about potential plot developments and their expressed preferences for these anticipated scenarios, even when such outcomes are not directly linked to the current storyline. Finally, topic-5 comments align with the type of participatory responses involving negative character evaluation. These comments reflect readers' negative judgments of the characters' actions.

Moreover, if a consumer decides to browse the chapter list first instead of reading the following chapter, she would be able to skim through the titles of all the chapters in the current book before determining which chapter to purchase next. Therefore, the information embedded in the chapter names could affect her decision. However, not all chapters in a book possess an informative title. For example, some chapter titles simply reflect their positions in the book, such as "Chapter one", while others reveal their inherent plots. Hence, we calculated the proportion of the chapters with informative names (i.e., those revealing partial plots) as a proxy for the informativeness of each book's chapter names. Another factor that a consumer might consider is her current position in the whole book. If she is approaching the end of the book, she might be eager to know the ending and may skip more chapters. We, therefore, measured consumers' current position by calculating the fraction of the number of chapters up to the focal chapter over the total number of chapters in the focal book.

We then report the summary statistics for each genre in Table 5.1. The platform categorizes e-books into four genres, i.e., male sensational fiction, female sensational fiction, gender-neutral fiction, and teen fiction. Among the four genres of books, female sensational fiction has the largest share, followed by teen fiction, male fiction, and gender-neutral fiction. Consumers, on average, skip more chapters when reading male fiction, while consumers of all four genres exhibit a high variance in the number of skipped chapters. Among the five topics clustering the in-chapter comments, comments pressuring the author to post new chapters are posted most frequently. The chapter prices of gender-neutral fiction are comparably higher, which, according to the platform pricing rules[5], implies such books possess relatively longer chapters. Finally, the chapter name informativeness is high across all four book genres, indicating a large proportion of chapters with meaningful titles.

[5] According to the platform, they set up the price for each book per chapter within the range between 0 CNY and 1 CNY, where the precise chapter price for each book is set based on the number of words in the chapter.

Table 3.1: Summary Statistics of the data

Variables	Male Sensational Fiction	Female Sensational Fiction	Gender-neutral Fiction	Teen Fiction
Distribution	0.21	0.32	0.16	0.31
Fraction of consumers skipping chapters	0.90	0.95	0.95	0.97
Average number of consumers' skipped chapters				
Mean	11.00	3.66	2.69	2.46
SD	48.22	24.03	6.56	7.98
Number of Topic 1 comments per chapter				
Mean	1.3	0.15	0.05	5.35
SD	1.25	0.14	0.38	20.36
Number of Topic 2 comments per chapter				
Mean	0.18	2.14	1.18	4.87
SD	1.31	2.67	2.53	34.19
Number of Topic 3 comments per chapter				
Mean	2.77	4.43	10.13	14.48
SD	35.27	12.25	21.33	69.74
Number of Topic 4 comments per chapter				
Mean	0.45	0.49	1.49	2.33
SD	4.56	1.75	2.82	8.36
Number of Topic 5 comments per chapter				
Mean	4.16	1.14	2.02	10.75
SD	17.55	3.89	6.29	48.53
Price per chapter				
Mean	0.02	0.03	0.22	0.05
SD	0.05	0.066	0.44	0.15
Chapter name informativeness				
Mean	0.99	0.97	0.89	0.80
SD	0.01	0.16	0.28	0.36

3.3 Model

In this section, we develop a structural model that captures consumers learning about e-book quality based on their direct and indirect reading experience. Specifically, when a consumer starts to read a new book, she faces imperfect information and is uncertain about its true quality. She then updates her belief on the quality by reading the book's new chapters and the embedded in-chapter comments left by previous readers. At the end of each chapter, she makes subsequent purchase decisions based on her up-to-date perceived quality of the book.

3.3.1 Bayesian Learning Process

First, we model how a consumer i updates her belief of the quality of an e-book m of genre j based on her previous purchases of the chapters of this book. As detailed above, the true quality of an e-book, α, is usually not perfectly accessible due to the risky nature of experience goods. Following the learning literature, we assume that the consumer is a Bayesian learner, not memoryless. Hence, we can formulate the consumer's updating process of book quality via a Bayesian learning process.

In a Bayesian learning framework, although the true product quality is improbable to observe beforehand, consumers of such products are exposed to specific signals and, therefore, able to learn the product's true quality over time through a Bayesian learning mechanism. Building on this framework, we formally develop the model for a consumer i in our context. We assume that books of each of the four genres have a unique true quality level, denoted as α_j for genre j, and are unknown to the consumer initially. During the subsequent reading process of chapters t ($t = 1, 2, ..., n_m$, where n_m denotes the total number of chapters in book m) of book m, consumer i receives signals reflecting the true quality of the book, generated from both her direct reading experience of the chapter and the indirect reading experience of previous readers conveyed in their in-chapter comments. We then develop the following model elucidating how the consumer learns the true quality levels from these two sets of signals.

Learning via Reading Experience Signal

In the present research context, consumers' direct reading experience of each chapter could generate a signal, denoted by $S_{im[j]t}$. However, such signal value has some randomness and therefore cannot reflect the precise true quality for several reasons. Firstly, the book quality may not be stable across all chapters. Some chapters may be more attractive than others due to plot design or the imperfection of the author's writing ability. Moreover, consumers' subjective reading experience and feelings about the book may not be the same every time they read it, resulting in random shocks. Hence, the signal provides certain information about the true quality of the book with random errors, $\delta_{im[j]t}$. However, consumers may perceive signals generated by reading books of different genres with diverse uncertainty levels. Therefore, we assume that the random noise of the signal, $\delta_{im[j]t}$, is drawn from a normal distribution with mean zero and variance τ_j^2, which is specific to books under genre j. Such a signaling mechanism indicates that although individual past reading experience induces signals around the true quality of the book, they are not precise.

We then formulate the signal value distributions received by consumer i as follows:

$$\begin{aligned} \text{Noise of Signal: } & \delta_{im[j]t} \sim N(0, \tau_j^2), \\ \text{Signal: } & S_{im[j]t} = \alpha_j + \delta_{im[j]t}, S_{im[j]t} \sim N(\alpha_j, \tau_j^2) \end{aligned} \tag{3.1}$$

Learning via Social Listening Signal

In addition to the chapter's content, the indirect reading experience of previous readers conveyed in the in-chapter comments may also generate signals reflecting the book's true quality. However, comments addressing different topics may be perceived as delivering different indirect experience. We thus use the volume of in-chapter comments across the five topics as we discovered in Section 3.2 as a proxy of the signal value generated by different indirect reading experience. We then develop the stochastic process for volume of topic-k in-chapter comments that consumers use to infer book quality as follows:

$$ln(1 + Bul_{im[j]t,k}) = Bul^M_{m[j],k} + \omega_{im[j]t,k},\ \omega_{im[j]t,k} \sim N(0, \sigma^2_{\omega,k}) \tag{3.2}$$

where $Bul_{im[j]t,k}$ denotes the number of the topic-k in-chapter comments faced by consumer i when reading chapter t of book m of genre j, $Bul^M_{j,k}$ denotes the mean of the log volume of the comments, and $\omega_{im[j]t,k}$ denotes a stochastic term that is i.i.d. over time. Consumers believe that, in the market equilibrium, the mean log comment volume is related to book quality according to the relation:

$$Bul^M_{m[j],k} = Bul_{0,k} + \phi_k * \alpha_j + \eta_{j,k},\ \eta_{j,k} \sim N(0, \sigma^2_{\eta,k}) \tag{3.3}$$

where $\eta_{j,k}$ denotes the deviation of book genre j from the typical topic-k-comment-quality relationship [6]. Combining the above two equations, for topic-k in-chapter comments, we have:

$$ln(1 + Bul_{im[j]t,k}) = Bul_{0,k} + \phi_k * \alpha_j + \eta_{j,k} + \omega_{im[j]t,k} \tag{3.4}$$

[6] $\omega_{im[j]t,k}$ captures the variability of the volume of the k-topic in-chapter comments, whereas $\eta_{j,k}$ captures how consumers perceive the signaling ability of the k-topic in-chapter comments in genre-j books.

We will estimate $Bul_{0,k}$, ϕ_k, $\sigma_{\omega,k}$, $\sigma_{\eta,k}$, and a set of $\eta_{j,k}$. Obviously, we cannot estimate both $Bul_{0,k}$ and a value of $\eta_{j,k}$ for each genre, so we restrict that $\eta_{j,k}$ are mean zero across genres for each k.

Consumer Learning about Book Quality

Now we form consumer i's learning process of book quality from the above two sets of signals. Before reading a new book of genre j, consumer i starts with prior beliefs about the book's quality, $A_{0m[j]}$, and mean log volume of the embedded topic-k in-chapter comments, $Bul^M_{0m[j],k}$. Similar to true quality, consumers may hold diverse prior expectations for books of different genres. To accommodate such a situation, we assume consumer prior belief, $A_{0m[j]}$, to be normally distributed with mean α_{0j}, which is distinctive to books of genre j, and variance σ_0^2, which is consistent across genres. The prior belief distributions are formally shown in (3.5).

$$A_{0m[j]} \sim N(\alpha_{0j}, \sigma_0^2) \text{ for j=1,...,4} \tag{3.5}$$

Consumers' prior beliefs about the mean log volume of in-chapter comments may also vary across different topics. Hence, we assume the prior distribution of mean log volume of topic-k in-chapter comment as follows:

$$Bul^M_{0m[j],k} \sim N(Bul_{0,k} + \phi_k \alpha_{0j}, \phi_k^2 \sigma_0^2 + \sigma_{\eta,k}^2) \text{ for k=1,...,5 and j=1,...,4} \tag{3.6}$$

Let $Bul^M_{im[j]t,k}$ and $\alpha_{im[j]t}$ denote consumer i's prior means for mean log volume of topic-k comments and quality of genre-j books, respectively. At t=0, these are $Bul^M_{im[j]t,k} = Bul_{0,k}$ and $\alpha_{im[j]0} = \alpha_{0,j}$. Given the prior belief and individual experience, consumer i then updates her belief about the book quality in a Bayesian fashion. We derive the posterior belief of consumer i following DeGroot (2005). Specifically, because the consumer prior belief (3.5, 3.6), the experiential signal (3.1), and the social learning signal (3.3) are all normally distributed, consumer i's posterior belief about the quality of the book m and the mean log volume of topic-k comments that are updated at the end of chapter t, also follow normal distributions with respective means $\alpha_{im[j]t}$ and $Bul^M_{im[j]t,k}$, as well as respective variances $\sigma^2_{\alpha_{im[j]t}}$ and $\sigma^2_{Bul_{im[j]t,k}}$. The updating mechanism of the posterior means and variances is shown in the following equations.

$$\alpha_{im[j]t} = \alpha_{im[j]t-1} + \sum_{k=1}^{5} [ln(1+Bul_{im[j]t,k}) - Bul^M_{im[j]t-1,k}] \cdot K^{Bul_kQ}_{im[j]t} + \beta \cdot (S_{im[j]t} - \alpha_{im[j]t-1}),$$
$$Bul^M_{im[j]t,k} = Bul^M_{im[j]t-1,k} + [ln(1+Bul_{im[j]t,k}) - Bul^M_{im[j]t-1,k}] \cdot K^{Bul_k}_{im[j]t},$$
$$\sigma^2_{\alpha_{im[j]t}} = [\frac{1}{\sigma^2_{\alpha_{im[j]t-1}}} + \frac{1}{\tau_j^2} + \sum_{k=1}^{5} \frac{\phi_k^2}{\sigma^2_{\eta,k} + \sigma^2_{\omega,k}}]^{-1}, \sigma^2_{Bul_{im[j]t,k}} = [\frac{1}{\sigma^2_{Bul_{ijt-1,k}}} + \frac{1}{\sigma^2_{\omega_k}}]^{-1} \tag{3.7}$$

where,

$$K^{Bul_k}_{ijt} = \frac{\sigma^2_{Bul_{ijt-1,k}}}{\sigma^2_{Bul_{ijt-1,k}} + \sigma^2_{\omega,k}}, K^{Bul_kQ}_{ijt} = \frac{\frac{\phi_k}{\sigma^2_{\eta,k}+\sigma^2_{\omega,k}}}{\frac{1}{\sigma^2_{\alpha_{im[j]t-1}}} + \sum_{k=1}^{5} \frac{\phi_k^2}{\sigma^2_{\eta,k}+\sigma^2_{\omega,k}} + \frac{1}{\tau_j^2}}, \beta = \frac{\frac{1}{\tau_j^2}}{\frac{1}{\sigma^2_{\alpha_{im[j]t-1}}} + \sum_{k=1}^{5} \frac{\phi_k^2}{\sigma^2_{\eta,k}+\sigma^2_{\omega,k}} + \frac{1}{\tau_j^2}} \tag{3.8}$$

Here $K^{Bul_k}_{ijt}$ and $K^{Bul_kQ}_{ijt}$ are the Kalman gain coefficients. Notably, $K^{Bul_kQ}_{ijt}$ captures how the consumer revises her perceived quality of genre-j book in response to the change in comment volume.

This posterior belief formulated by consumer i at the end of chapter t would also be her prior belief at the beginning of the next chapter. The same Bayesian learning-updating mechanism is then repeated until the consumer's perceived quality converges to the true quality of the book. Through the subsequent reading process of more chapters, the consumer's perceived variances of the book quality and the in-chapter comments' volume would reduce to zero, indicating that the consumer can ascertain the book's true quality and mean comments' volume.

3.3.2 Utility models

In this section, we specify our utility-maximization-based approach structuring how a consumer makes purchase decisions based on her current belief of the product quality. We start by clarifying a consumer's general 2-stage decision-making procedure in our context. At the end of each chapter read by the consumer, she faces three options at the first stage: reading consecutively, browsing the chapter list, or quitting the current book. The decision made by the consumer at this stage is formed based on her current information set, i.e., her belief about the book quality, the price that she needs to pay for the next chapter[7], and the total amount of money that she has paid for the focal book so far. The second stage arises if she chooses to return to the chapter list. She then browses the chapter names in the list and determines which following chapter to purchase next in the presence of the information implied by the chapter names and her current position in the book. This decision-making process is then repeated at the end of each chapter the consumer reads.

With this procedure, we first formulate the utility functions of consumer i at stage 1 at the end of chapter t of book $m[j]$ as follows. Given consumer i's current information set, her utility to read continuously (denoted by $U_{im[j]t1}$), i.e., to purchase chapter $t+1$, is shown below:

$$U_{im[j]t1} = \beta_{00} \cdot A_{im[j]t} + \beta_1 \cdot Price_{im[j]t} + \beta_2 \cdot TotalSpend_{im[j]t} + \varepsilon_{im[j]t1} \tag{3.9}$$

where $A_{im[j]t}$ indicates consumer i's belief of the quality of book $m[j]$ at the end of chapter t, $Price_{im[j]t}$ indicates the amount of money that consumer i needs to pay for chapter $t+1$, and $TotalSpend_{im[j]t}$ indicates the total amount of money that consumer i has already paid for book k. To account for the skewed distribution of $TotalSpend_{im[j]t}$, we apply a log transformation to it and use the transformed variable. Finally, $\varepsilon_{im[j]t1}$ is a random shock known only to the consumer.

Similarly, the utility of consumer i to return to the chapter list of book $m[j]$ at stage 1, denoted by $U_{im[j]t2}$, is shown as $U_{im[j]t2} = \beta_{10} \cdot A_{im[j]t} + \beta_3 \cdot Price_{im[j]t} + \beta_4 \cdot TotalSpend_{im[j]t} + \varepsilon_{im[j]t2}$.

Following a random utility choice framework (e.g., McFadden (1974)), we then derive the

[7] After the consumer finishes reading a chapter, she will be asked whether to purchase the next chapter directly, presented with the price she would need to pay.

probabilities for the three choices made by consumer i at the first stage in Equation 3.10.

$$\begin{aligned}
Pr(Conti_{im[j]t}=1) &= \frac{exp(U_{im[j]t1})}{exp(U_{im[j]t1})+exp(U_{im[j]t2})+1},\\
Pr(Back_{im[j]t}=1) &= \frac{exp(U_{im[j]t2})}{exp(U_{im[j]t1})+exp(U_{im[j]t2})+1}\\
Pr(Quit_{im[j]t}=1) &= \frac{1}{exp(U_{im[j]t1})+exp(U_{im[j]t2})+1}
\end{aligned} \tag{3.10}$$

where $Conti_{im[j]t}$ indicates whether after finishing reading chapter t of book $m[j]$, consumer i determines to read chapter $t+1$, $Back_{im[j]t}=1$ indicates whether she decides to return to the chapter list, and $Quit_{im[j]t}$ indicates whether she chooses to quit reading book $m[j]$.

The second stage arises if consumer i returns to the chapter list. Given the information set provided by the list, she then determines which following chapter to purchase. She may still choose to read the consecutive chapter or skip a few chapters to read a later one. Hence, at stage 2, consumer i's choice comprises the number of chapters to skip, denoted by $N_{im[j]t}$. We first formulate her utility at this stage, $U_{im[j]t3}$, as follows:

$$U_{im[j]t3}=\beta_{20}\cdot A_{im[j]t}+\beta_5\cdot Informativeness_{im[j]t}+\beta_6\cdot Position_{im[j]t}+\varepsilon_{im[j]t3} \tag{3.11}$$

where $Informativeness_{im[j]t}$ indicates the proportion of the chapters of book $m[j]$ possessing a meaningful name, and $Position_{im[j]t}$ indicates the current position of consumer i, i.e., the place of chapter t in the whole book.

Following Yan and Tan (2014), we then model the choice of consumer i at stage 2 (i.e., the number of chapters to skip from chapter t), a count variable, to follow a negative binomial distribution (NB) given her utility. At this stage, the consumer may choose to read consecutively (i.e., skip zero chapters) or skip certain chapters. Thus, combining with the choice probabilities of consumer

i derived in the first stage, we formulate her chapter selection choice as follows:

$$P(N_{im[j]t} = n) = \begin{cases} Pr(Conti_{im[j]t} = 1) + Pr(Back_{im[j]t} = 1) \cdot G(0) & \text{when n=0} \\ Pr(Back_{im[j]t} = 1) \cdot G(n) & \text{when n>0} \end{cases}$$
$$G(n) = \frac{\Gamma(\theta + n)\theta^{\theta}\lambda_{im[j]t}^{n}}{\Gamma(n+1)\Gamma(\theta)(\lambda_{im[j]t} + \theta)^{\theta+n}}, \lambda_{im[j]t} = exp(U_{im[j]t3}) \tag{3.12}$$

where θ is a parameter to capture possible over-dispersion in $N_{im[j]t}$.

3.3.3 Mundlak's approach

Although we controlled for various factors that may impact consumer utilities during their decision-making process, our model may still suffer from an endogeneity issue. To account for this problem, we apply a correlated random effects (CRE) framework developed by Mundlak (1978), as detailed in Appendix A.3. Following the CRE framework, we adjust our model specified in the previous section to mitigate the potential endogeneity concern. To this end, we first reform the utility functions of a consumer i to read the next consecutive chapter and to return to the chapter list at the end of chapter t of book $m[j]$ (i.e., stage 1 utilities), respectively, as follows:

$$\begin{aligned} U_{im[j]t1} &= \beta_{00} \cdot A_{im[j]t} + \beta_1 \cdot Price_{im[j]t} + \beta_2 \cdot TotalSpend_{im[j]t} + \beta_{16} \cdot \bar{\mathbf{X}}_{\mathbf{im[j]}} + \varepsilon_{im[j]t1} \\ U_{im[j]t2} &= \beta_{10} \cdot A_{im[j]t} + \beta_3 \cdot Price_{im[j]t} + \beta_4 \cdot TotalSpend_{im[j]t} + \beta_{26} \cdot \bar{\mathbf{X}}_{\mathbf{im[j]}} + \varepsilon_{im[j]t2} \end{aligned} \tag{3.13}$$

where $\bar{\mathbf{X}}_{\mathbf{im[j]}}$ indicates the averages of the potential endogenous variables in our models, i.e., the amount of money consumer i needs to pay for chapter $t+1$ and her current cost spent on book k. We then plug the expected adjusted utilities into Equation 3.10 to derive consumer i's choice probabilities at stage 1, and apply the rest of our model to the data.

3.4 Results

For the identification of our model, we fixed the true quality levels of books across all four genres to be 0 and the variance of consumers' prior beliefs about the book quality to be 1 during the estimation process. Hence, based on the Bayesian updating theory, the effect of the consumer's prior quality belief decreases over time, enabling the identifiability of the mean levels of consumers' prior quality belief and the signal variances. We then constructed the likelihood of our observed data as elaborated in Appendix A.4 and used the simulated maximum likelihood method to estimate the model, through implementing a Hamiltonian Monte Carlo (HMC) Algorithm (Duane et al. 1987)[8].

We report the estimates of the model in Table 3.2. First, we see that consumers have different prior expectations of the book quality across four genres. Before reading, consumers believe more in the quality of gender-neutral fiction, whereas the quality of teen sensational fiction is not very trusted. In addition, consumers learn the true quality of books across four genres through their direct reading experience at a different pace. The experiential signal variance of books clustered in genre 4 (i.e., teen romance fiction) is the largest, followed by genre 2 (i.e., female sensational fiction), genre 1 (i.e, male sensational fiction) and genre 3 (i.e., gender-neutral fiction). This result indicates that consumers perceive their experience in reading gender-neutral fiction the most consistent, whereas their reading experience of the chapters of teen fiction provides a more diverse signal of the book quality.

Furthermore, our model results illustrate how the consumer learns from in-consumption social listening. Our estimation of the slope within each comment-quality relationship gauges the consumer's interpretation of each topic within the in-consumption comments, which they utilize as signals of the book's quality. Positive values of ϕ_2, ϕ_3, and ϕ_5 indicate that, when encountering more in-chapter comments that make inferences based on current scenes, plead for the release of new chapters, or judge character behaviors negatively, the consumer would revise upward her perception of the book quality. These estimates align with our expectations. As elaborated in Section 3.2, topic-2 comments comprise previous readers' inferences based on the narrative, topic-3 comments explicitly express a strong narrative engagement of readers, and despite the use of neg-

[8]Compared to using a Gaussian random walk proposal distribution in the Metropolis-Hastings algorithm, HMC reduces the correlations between successive sample states such that fewer Markov chain samples are needed for convergence.

Table 3.2: Parameter Estimates[1]

Paramter	Estimate	Std. error
Consecutive Reading		
Price	0.21	0.18
TotalSpend	-1.22^{***}	0.16
Perceived Quality	4.68^{***}	0.42
Returning to Chapter List		
Price	0.33^{***}	0.11
TotalSpend	-2.42^{***}	0.30
Perceived Quality	3.73^{***}	0.34
Skipping Chapter		
Informativeness	-1.78^{***}	0.04
Position	5.78^{***}	0.18
Perceived Quality	-2.02^{***}	0.00
TotalSpend	-1.36^{***}	0.11
θ	0.01^{***}	0.00
Experiential Signaling Parameters		
α_{01}(Mean prior quality belief of Book Genre 1)	-110.18^{***}	14.76
α_{02}(Mean prior quality belief of Book Genre 2)	-113.10^{***}	16.13
α_{03}(Mean prior quality belief of Book Genre 3)	-68.96^{***}	14.20
α_{04}(Mean prior quality belief of Book Genre 4)	-122.70^{***}	15.40
τ_1^2(Experiential Signal Variance of Book Genre 1)	10.57^{***}	2.22
τ_2^2(Experiential Signal Variance of Book Genre 2)	18.27^{***}	7.63
τ_3^2(Experiential Signal Variance of Book Genre 3)	4.54^{***}	1.02
τ_4^2(Experiential Signal Variance of Book Genre 4)	20.71^{***}	7.72
Social-Listening Signaling Parameters		
$Bul_{0,1}$(Intercept of Topic-1 Comment)	0.22^{***}	0.01
$Bul_{0,2}$(Intercept of Topic-2 Comment)	0.22^{***}	0.01
$Bul_{0,3}$(Intercept of Topic-3 Comment)	1.07^{***}	0.01
$Bul_{0,4}$(Intercept of Topic-4 Comment)	0.18^{***}	0.01
$Bul_{0,5}$(Intercept of Topic-5 Comment)	0.65^{***}	0.01
ϕ_1(Slope of Topic-1 Comment Signaling Equation)	-0.32^{***}	0.05
ϕ_2(Slope of Topic-2 Comment Signaling Equation)	4.85^{***}	0.24
ϕ_3(Slope of Topic-3 Comment Signaling Equation)	1.41^{***}	0.37
ϕ_4(Slope of Topic-4 Comment Signaling Equation)	-1.93^{***}	0.65
ϕ_5(Slope of Topic-5 Comment Signaling Equation)	0.50^{***}	0.75
$\sigma^2_{\eta,1}$(Variance of Genre-specific Constants)[2]	3.34^{***}	0.67
$\sigma^2_{\eta,2}$(Variance of Genre-specific Constants)	1.26^{***}	0.11
$\sigma^2_{\eta,3}$(Variance of Genre-specific Constants)	4.62^{***}	0.58
$\sigma^2_{\eta,4}$(Variance of Genre-specific Constants)	7.90^{***}	0.18
$\sigma^2_{\eta,5}$(Variance of Genre-specific Constants)	1.63^{***}	0.44
$\sigma^2_{\omega,1}$(Topic-1 Comment Volume Variability)	0.96^{***}	0.02
$\sigma^2_{\omega,2}$(Topic-1 Comment Volume Variability)	0.85^{***}	0.01
$\sigma^2_{\omega,3}$(Topic-1 Comment Volume Variability)	1.32^{***}	0.01
$\sigma^2_{\omega,4}$(Topic-1 Comment Volume Variability)	0.74^{***}	0.02
$\sigma^2_{\omega,5}$(Topic-1 Comment Volume Variability)	1.19^{***}	0.04

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

[2] *The genre-specific constants are presented in the full table in Appendix.*

ative emotional words, topic-5 comments suggest that previous readers were adequately engaged by the narrative to make judgments on character behavior. All these three topics of in-consumption comments serve as forms of active participation, indicating a successful delivery of a narrative experience by the chapter. These comments are then perceived by the current consumers as positive signals of the book's quality, as they indicate previous readers are deeply immersed in the story. On the contrary, the negative estimates of ϕ_1 and ϕ_4 imply that an increased volume of in-consumption comments containing solely happy emotional words or those depicting a desired hypothetical future scene could decrease consumers' perceived quality of the book. While topic-1 comments indicate that previous readers found amusement in certain scenes of the book, they comprise purely onomatopoeic representations of laughter. These expressions, while signaling merriment, are generally uninformative and might also hint at a temporal happy ending in the narrative, an element which is less appealing to readers (Reagan et al. 2016). Similarly, topic-4 comments reflect readers' wishful thinking regarding potential plot developments, which are not immediately related to the current storyline, suggesting that the present content may not be successfully engaging the readers. Therefore, rather than viewing these in-consumption comments as a form of active engagement, the current consumer is inclined to perceive them as negative indicators of the book's lack of appeal.

In addition, our estimates of σ_η^2s and σ_ω^2s capture how the consumer perceives the noise in the in-consumption comment signals and the variability of the comment volumes, respectively. As shown in the table, consumers perceive the least noise in the topic-2 comment-volume-quality relationship, whereas the topic-4 comment-volume-quality relationship exhibits the highest noise. The volume of topic-2 comments also varies the least over chapters. These factors suggest that the volume of topic-2 comments would serve as a more effective signal of the book quality among the five social-listening signals.

Our model results also show that the informativeness of chapter names negatively correlates with consumers' utility to skip more chapters, whereas a close-to-end position of the focal chapter enables consumers to skip more chapters. A list of more chapters with informative names may be more attractive to consumers, who, therefore, may be more likely to skip fewer chapters without missing essential plots. Meanwhile, when a consumer moves further in a book, she may be more anxious to read its ending and urged to skip more chapters to approach the end. Additionally, we find that consumers' perceived book quality positively affects their utility to read consecutively and return to the chapter list, indicating a decreased probability of quitting. The price of the next chapter shown to consumers is not a significant determinant in driving them to read consecutively but positively correlates with their utility to browse the chapter list. With all the chapter prices lower than one Chinese dollar, the consumer tends not to consider it an essential factor directly affecting her intention to read the following chapter. Meanwhile, a higher price still indicates that the consumer needs to pay more for the next chapter, which would lead to an increase in her intention to browse the chapter list first. However, the total cost spent on the focal book discourages consumers from both reading continuously and browsing the chapter list.

3.5 Policy Simulation

A key advantage of structural models is that they can be used to perform counterfactual policy experiments because users' utility function estimated in the models is invariant to changes in input variables (Erdem and Keane 1996). The Bayesian learning model we've developed offers insights into how learning from both direct experience and in-consumption social listening can mitigate the uncertainty associated with a new book as one progresses through reading it. Of the two types of signals, promoting experiential learning signals proves to be more challenging. This is because it requires enhancing the author's capacity to deliver a consistent and stable reading experience throughout chapters. Hence, focusing on enhancing the in-consumption social listening signals that are generated by various topics of in-consumption comments is more practical. Following this, we execute a series of policy simulations rooted in our estimated Bayesian learning model to measure the impact of social listening on consumers' reading behavior. As delineated in Section 3.3, a consumer's learning process regarding a new book can be influenced by both the volume of in-consumption comments spanning five topics and their variability. In line with this, we simulate the potential effects of alterations in these two variable groups on the likelihood of consumers reading without skipping.

3.5.1 Validation of the Fitted Model

Before executing new policy simulations, we begin with demonstrating the validity of our estimated Bayesian learning model. Specifically, we simulate consumers' chapter selection behavior based on our fitted model and the original data, to see if we could recover consumers' actual purchase decisions. The rooted mean squared error (RMSE) of our model's predicted number of consumers' skipped chapters is 3.36. We further examine the ability of our model to recover consumers' non-skipping behavior, and we found that the overall accuracy is 95.11%. Both metrics suggest that our estimated model is a valid fit for the data.

3.5.2 Increasing the In-consumption Comment Volume

We then double the volume of in-chapter comments for each of the five topics, respectively. The resulting changes in the average non-skipping probability of consumers are shown in the second column of Table 3.3. Our findings indicate that increasing the volume of in-consumption comments causes a corresponding change in consumers' intention to continue reading, in line with the trends indicated by the slopes in the respective comment-volume-quality relationships. Specifically, among the five topics of in-consumption comments, amplifying the presence of topic-2 comments within chapters would yield the highest increase in the probability of readers continuing without skipping, with an increase of 4.56%.

Table 3.3: Policy Simulation Results

	Change of Non-skipping Probability	
In-consumption Comments	**Policy 1: Double Volume**	**Policy 2: Half Variability**
Topic-1	−2.81%	−14.79%
Topic-2	4.56%	40.98%
Topic-3	4.07%	26.34%
Topic-4	−4.02%	−30.26%
Topic-5	2.19%	15.18%

3.5.3 Decreasing the In-consumption Comment Volume Variability

Finally, we decrease the variability of the in-chapter comment volume for each of the five topics by 50%, respectively. Specifically, we followed the procedure developed by Erdem and Swait (1998) to perform the simulation, as detailed in Appendix A.5. The simulation results are shown in the third column of Table 3.3. With a decreased variability, the comment volume becomes a more accurate signal of the book's quality. When the commentary topics are generally perceived positively, such as topics 2, 3, and 5, greater consistency leads to a notable rise in the likelihood of continuous reading by consumers. In contrast, for topics 1 and 4, which may be viewed less favorably, increased consistency in comments would likely decrease the probability of a reader choosing to continue without skipping. Notably, improving the consistency of in-consumption comments is more effective than merely increasing their volume, as it triggers a more substantial shift in consumers' continuous reading probabilities.

3.6 Conclusion

We present one of the first comprehensive empirical evidence unveiling how consumers learn the true quality of experience goods from in-consumption social listening, accompanied by their direct consumption experience. Specifically, we focus on the context of online reading, where readers' in-consumption participation is captured via a novel in-chapter online commenting feature. Through developing and estimating a multi-signal Bayesian learning model, our findings contribute to the literature on in-consumption social listening, narrative participation, and online media business models.

First, our research expands the trending in-consumption social listening literature. With the recent development of a novel live commenting feature by online media, such as online reading platforms and video streaming websites, live comments, a new form of in-consumption data becomes available. These comments resonate with traditional online reviews but differentiate in terms of providing a continuous, immediate, and spontaneous flow of consumers' reactions triggered by temporal variation in product content. Despite the substantial potential economic value of such in-consumption data, existing literature primarily highlights its ability to predict consumer satisfaction post-experience (Zhang et al. 2020). Our study adds to the literature by identifying the impacts of these in-consumption comments on consumers' evolving perception of product quality, leading to a shift in their purchase decisions made throughout the consumption process.

Second, our research enhances existing literature on narrative participation. Previous studies suggest that a successful delivery of narrative experience (that is, consumers' orienting responses are elicited by temporal changes in the narrative) would lead to active in-consumption participation of consumers (Lynn 2013, Bezdek et al. 2013). However, in our setting of live commenting, the in-consumption comments may not be only generated by active participation (Berger 2014), especially when the content is less attractive; moreover, they can be subject to different interpretations by consumers who read them. Our findings on how consumers infer product quality using different categories of in-consumption comments contribute to the literature by addressing this underexplored question. We show that not all in-consumption comments are interpreted by consumers as a positive signal of product quality. While certain comments may indicate that readers are triggered with emotional reactions by the scenarios, depending on the topic, consumers facing more of these comments may revise downwards their perceived product quality.

Third, our study within the growing pay-by-content model expands the literature on business models adopted by online platforms. While resonating with the well-documented unbundling and pay-per-use model (Stremersch and Tellis 2002, Gilbert et al. 2014), the pay-by-content model grants consumers with higher flexibility through breaking down a comprehensive product, such as a book, into interrelated segments, as well as allowing consumers to consume these segments in sequence without any time constraints, at a relatively low cost. Our research contributes to the literature by identifying the factors driving consumers' decisions within this new model.

Our results provide a few managerial implications. Firstly, the variances of experiential signals vary from genre to genre. Except for gender-neutral fiction, the book content of other genres generates a less accurate quality signal. Therefore, authors specializing in other genres may polish their posted chapters to provide consumers with a more consistent reading experience throughout the book. Secondly, our policy simulation results show that increasing the volume of the in-chapter comments that serve as positive quality signals could enhance consumers' intention to read continuously. Similarly, reducing the variability of these signals would improve their accuracy, leading to an even higher increase in the probability of readers continuing without skipping. Hence, to promote future continuous reading, the platform may encourage consumers to not only post more of these "favorable" in-chapter comments but also ensure they do so with consistent frequency across chapters. This may be achieved through various motivation mechanisms, e.g., a high-quality recognition of such comments or a monetary incentive such as vouchers. Lastly, we find that a consumer would be more likely to skip fewer chapters with a more informative chapter list. The platform may thus enable the authors to name their chapters in a more informative fashion instead of as a simple indicator of the chapter's position.

This research has several limitations. Firstly, due to data limitations, we didn't account for consumer heterogeneity when modeling their utilities toward different choices, which may be taken into consideration if the demographic data of consumers is available. Secondly, we do not have access to the engagement measures of consumers with the in-chapter comments. Future research may examine how engagement mechanisms affect the weight of different comments. Finally, the current study focuses on the direct impact of in-chapter comments on consumer decisions. If obtaining data that reflects the precise position of the comments, a future study can incorporate the interplay between the comment and the focal content.

Chapter 4

KILLING NOT JUST WEEDS: UNEXPECTED CONSEQUENCES OF COMBATING MISINFORMATION

4.1 Introduction

The fast spread of misinformation has become a global problem. Defined as false or misleading information that does not align with expert consensus or concrete and observable evidence (Vraga and Bode 2020), misinformation can lead to severe consequences if propagated on social media. Ranging from conspiracy theories to unproven or harmful remedies such as disinfectant injections to treat coronavirus patients, the spread of coronavirus rumors has led to injuries and deaths (Sheera Frenkel and Zhong 2020, Pennycook et al. 2020b, Delirrad et al. 2021). Another controversial topic filled with misinformation is vaccines (Bellaby 2003). In 1998, Wakefield and colleagues first claimed that autism and the MMR vaccine are linked (Wakefield et al. 1998). Although epidemiological studies later confirmed no link between increasing autism diagnoses and the introduction of the MMR vaccine, widespread concern lingers, especially among parents (Bellaby 2003). Such vaccine hesitancy arising from false information leads to a significant increase in annual measles cases, which in turn leads to an additional US$2.1 million in public sector costs (Lo and Hotez 2017).

Given these substantial public health and economic consequences driven by online misinformation, this study investigates the effectiveness of a potential weapon that may help fight against the "infodemic." Specifically, we focus on the misinformation policy implemented by Twitter. To combat proliferating misinformation, Twitter proposed an intervention in May 2019 that helps users find reliable information about measles and vaccines. In January 2020, Twitter expanded the scope of the intervention to COVID-19 to control the increasing misinformation on the topic. The intervention involves a search prompt; when a user searches for specific keywords such as covid, measles, or vaccine, Twitter generates a prompt titled "Know The Facts," which appears at the top of the search results. For example, when a user searches for COVID, the prompt shows the sentence "To make sure you get the best information on the coronavirus (COVID-19), resources are available from the Centers for Disease Control and Prevention (CDC)," followed by a link to the CDC website, a reliable public health information source.

An effective countermeasure should reduce misinformation and, at the same time, facilitate the spread of true information. Although the previous literature has examined the effectiveness of the interventions on misinformation cascade (Chiou and Tucker 2018, Hwang and Lee 2021), to the best of our knowledge, the effect of such implementations on the spread of true information remains unclear. Furthermore, there is a significant mismatch between the actual misinformation countermeasures utilized by social platforms and those studied by the research community (Courchesne et al. 2021). Including Twitter's policy, which we study in this research, around 50% of the interventions implemented by social platforms are a form of redirection (i.e., redirecting users to a trustworthy information source). However, a majority of previous studies inspect countermeasures that focus on misinformation disclosure and content labeling (Yadav 2021). To fill the gap in the literature, our study focuses on empirically unveiling the effects of Twitter's redirecting intervention on the spread of true information.

Based on extant studies, the intervention's impact on true information diffusion is unclear. In a lab experiment, Roozenbeek et al. (2021) examined whether participants' intention to share true information changes if they are implicitly nudged to pay more attention to the content accuracy. Specifically, they asked participants to rate the truthfulness of an unrelated statement before participants are exposed to COVID-19 related claims. Roozenbeek et al. (2021) found that such implicit nudging doesn't increase participants' intention to share true information. Yet, another lab experiment found that similar interventions significantly improve participants' intention to share true information (Pennycook et al. 2020b). Although the context was different (i.e., a lab setting) from ours and the intervention was much more subtle than the Twitter intervention, the mixed findings of these related studies suggest that Twitter interventions may or may not effectively facilitate true information diffusion - an uncertainty that calls for further empirical investigation.

We utilize a unique quasi-experiment setting and quantify the policy's impact on both true information and misinformation diffusion. According to Twitter, tweets addressing information on COVID-19, measles, and vaccines are affected by the policy, whereas this policy does not affect tweets on other health topics such as cancer. Hence, information regarding COVID-19, measles, and vaccines forms our treatment group, and health information on other topics forms our control group. For our empirical analysis, we compile the following data. First, utilizing Snopes.com (a fact-checking website), we collect a set of verified true and false claims on the affected as well as unaffected health topics. Then, using Twitter API, we extract tweets that contain the claims we collected.

We find that, while cascades of false information are the most suppressed, Twitter's policy also has an undesirable suppressive effect on the spread of true information. After the implementation of the policy, the cascade of true information is suppressed in terms of the number of retweets (a 24.0% reduction), the number of replies (a 15.6% reduction), and the number of likes (a 24.6% reduction). To understand this unexpected finding, we dive deep to uncover the mechanisms behind the suppression. We suspect that true news is also suppressed because people might have difficulty discerning the truthfulness of the information. To empirically check this possibility, we collected people's perceived truthfulness of the claims utilizing Amazon Mechanical Turk. We then empirically examined the moderating effect of people's perception of how Twitter's intervention impacts the diffusion of true and false information. Consistent with our expectation, the analysis reveals that Twitter's intervention is more effective for the information that is perceived to be false by people: Information is more suppressed if people think it is fake. Due to the difficulty of discerning the actual truthfulness of information (i.e., true news is not always perceived as true news), people's sharing of true information also decreased after the intervention. We further demonstrate this mechanism by looking into the effects of the policy on the authoritative accounts verified by Twitter, whose tweets were found to diffuse even more after the intervention. The results suggest that, because people struggle to discern the truth, they tend to pay more attention to the identity of the accounts posting new information, which serves as a signal of truthfulness.

4.2 Empirical Framework

4.2.1 Research Context

To fight against misinformation about measles and vaccines, Twitter announced the initial launch of a misinformation policy on May 10, 2019 (Harvey 2019). The policy works in the following way: When a user searches for topics containing specific keywords where misinformation is rampant, Twitter generates a prompt with a heading of "Know the Facts." The prompt appears at the top of the user's search results and contains a link to a trustworthy information source. On January 29, 2020, in order to combat massive falsehoods arising from the outbreak of COVID-19, Twitter expanded its "Know the Facts" search prompt by including COVID-19 related keywords in its trigger words list. This misinformation policy provides us with a quasi-experiment setting to examine its impacts on the distribution of true and false information, in that the policy is only applicable to specific topics; that is, measles, vaccines, and COVID-19. Figure 4.1 shows a screenshot of the prompt generated by the search of "covid," which is a trigger word related to COVID-19 topics. In the prompt, Twitter provides users with clear guidance about where and how to find reliable information about the searched topic by displaying the link to trustworthy sources (i.e., "vaccines.gov" and "CDCGov").

4.2.2 Data

To empirically examine the effects of Twitter's policy on information diffusion, we needed to collect true and false information from Twitter and capture the corresponding cascades. Since Twitter does not manually inspect the accuracy of each individual tweet, we followed the subsequent steps to identify true and false tweets from the large pool: We first collected claims whose truthfulness has already been verified by reliable sources (i.e., fact-checking organization), and then applied various approaches to collect tweets that make same claims.

Figure 4.1: Search prompt generated by Twitter's policy

Claim Collection

Although it is infeasible to research every piece of information that spreads online, many fact-checking platforms such as Snopes[1] make continuous efforts to inspect the truthfulness of questionable claims. We therefore utilized Snopes as a source to find true and false information. Snopes has developed a rating system to help users quickly ascertain the credibility of a claim, categorizing each claim into one of the following fact-check ratings by the platform[2]: "False," "Mostly False," "Mixture," "Mostly True," and "True." Figure 4.2 shows a sample fact-checked claim by Snopes. A fact-check result includes a summary of the claim, followed by the rating provided by the platform. From Snopes, we scraped all the health-related claims (e.g., COVID-19, measles, vaccines, cancer, etc) that are labeled as one of the five ratings. For our analysis, we grouped all claims with a rating of "False" or "Mostly False" as False and those with a a rating of "True" or "Mostly

[1] https://www.snopes.com

[2] https://www.snopes.com/fact-check-ratings/

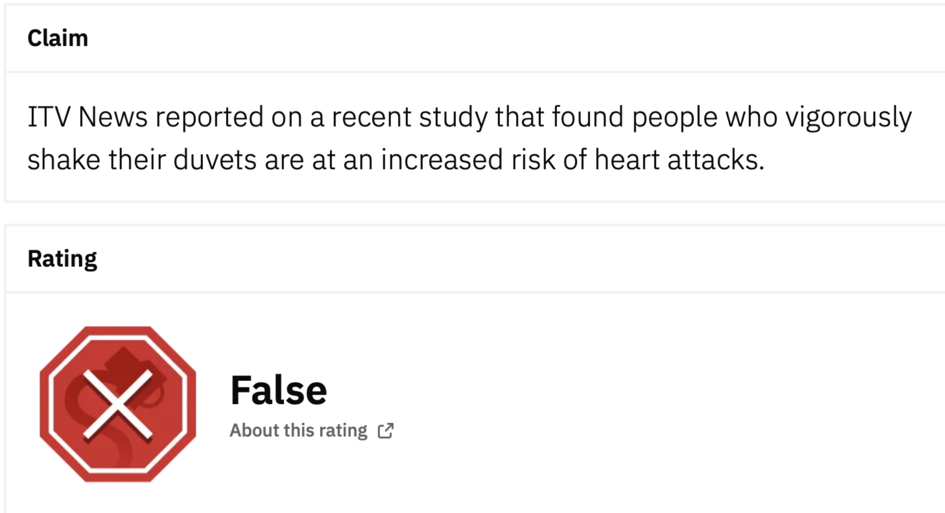

Figure 4.2: A sample fact-checked claim on Snope

True" as True[3] (Vosoughi et al. 2018). In this study, we chose to focus on the true and false claims but not the mixed claims (i.e., claims rated as Mixture) due to the ambiguity in the truthfulness of their embedded information.[4] Among the 852 unique claims we obtained, 565 claims belong to the treatment group, which contains information about measles, vaccines, or COVID-19. The remaining claims belong to the control group, which features other health-related topics. 428 claims are rated as True and 424 claims are rated as False.

Associated Tweet Detection

To capture the diffusion of true and false information on Twitter, we next identified tweets that contained the 852 claims we collected from Snopes. While Snopes provides a summary of each claim and whether the claim is true or false, Snopes does not provide the link to the source of

[3] We followed Vosoughi et al. (2018) to group the claims. In addition, according to the explanations for each rating provided by Snopes https://www.snopes.com/fact-check-ratings/, claims that are rated as "Mostly True" ("Mostly False") comprise trivial correct (incorrect) content that does not affect the main information conveyed by the claims. Therefore, we can safely group such claims based on the truthfulness of their main content.

[4] According to Snopes, mixed claims indicate the claims that contain significant elements of both truth and falsity such that they could not fairly be described by either true or false.

inspected claims. Hence, to obtain the source information of each claim, we first searched tweets that contain 852 claims. Specifically, we extracted tweets containing each claim topic's relevant keywords. Due to the massive size of tweets that satisfy this keyword search, we performed a daily sampling: For each covered health topic (e.g., COVID-19, measles, vaccines, cancer, etc.), we collected the first 2,000 tweets containing related keywords daily during our empirical period (May 2017 to May 2021).

Although these tweets address the topics covered by the claims, we utilized several text mining techniques to filter the tweets further, because the full-text content of the tweets might not convey the same information as expressed in the claims. For this filtering step, we first used the fastText algorithm, a state-of-the-art method created by Facebook's AI (Artificial Intelligence) research lab to learn word embeddings, to convert the claims and the collected tweets respectively to 100-dimension vectors that captured their semantic content (Bojanowski et al. 2016). Extending the Word2Vec algorithm, fastText learns the word embeddings on a more granular level; that is, instead of learning vectors for words directly, fastText represents each word as an n-gram of characters and trains a skip-gram model to learn the embeddings. Therefore, fastText is capable to capture rare words in the text, such as misspelled words, which are common in a casual writing context like Twitter.

We then applied two widely used metrics; that is, ROUGE scores and cosine similarity, to compare the semantic distance between the claims and the tweets (Lin 2004, Huang et al. 2008). The ROUGE score allows us to measure the semantic distance between the claims and tweets by capturing the fraction of overlapping words in the two pieces of text for comparison. We further calculated the cosine similarity using the numeric embeddings of the text to capture the semantically similar information with different wordings. Specifically, for each claim, we recursively examined the ROUGE recall score and the cosine similarity of each corresponding tweet. If the

ROUGE recall score was higher than 0.7[5] and the similarity was higher than 0.9[6], the tweet was assumed to be addressing the claim accurately; otherwise, it was discarded. After filtering, 1,688 tweets are identified that contain 852 claims. We refer to these tweets as seed tweets.

After identifying the seed tweets, we then followed the approach in Vosoughi et al. (2018) to extract the external links embedded in the tweets which direct to the original sources of the claims. We then passed these external links to Twitter's API to extract all English-language original tweets containing any of these links that were posted during our empirical period. To make sure these tweets were in fact addressing the original claims, we again checked content similarity using the two aforementioned metrics; that is, ROUGE scores and cosine similarity. We extracted 13,956 tweets following this procedure. For each of the tweets, we collected the post date, text content, additional entities (e.g., hashtags, URLs, etc.), the diffusion metrics of its corresponding cascade provided by Twitter (i.e., number of retweets, quotes, likes, and replies), and the user information of its publisher.

After all of the data processing and dropping the duplicates, we obtained a dataset of 11,694 unique tweets that were posted within our empirical time window (May 2017 to May 2021), out of which 3,443 tweets (addressed the claims that) were rated as True and 8,251 tweets (addressed the claims that) were rated as False.

4.3 Empirical Model and Results

4.3.1 Empirical Model: Difference-in-Differences (DiD)

To inspect the causal effects of Twitter's policy on information, we implemented a Difference-in-Differences (DiD) analysis, which is a popular framework for treatment effect estimation with

[5]ROUGE-N is computed as $ROUGE-N = \frac{\sum\limits_{S \in References} \sum\limits_{gram_n \in S} Count_{match}(gram_n)}{\sum\limits_{S \in References} \sum\limits_{gram_n \in S} Count(gram_n)}$, where n indicates the length of the n-gram. In this study, we set $n = 1$. Previous studies show that a state-of-the-art summary model usually achieves a ROUGE-1 score of approximately 0.519 (Gambhir and Gupta 2017). Therefore, the threshold of 0.7 that we set should be able to filter out unrelated tweets.

[6]Given the vectors of two pieces of text to compare, denoted by x and y, the cosine similarity is defined as $cos(x,y) = \frac{x \cdot y}{|x||y|}$, which approaches one when they are semantically similar. We then set the threshold to be 0.9, which is higher than the cosine similarity of relevant documents compared in previous studies (Lahitani et al. 2016).

a quasi-experiment setting (Heckman et al. 1997). The adoption of DiD framework requires the identification of a treatment group (which is affected by the treatment) and a control group (which is not affected). In our context, the treatment is the launch of Twitter's policy. The policy was first initiated on May 10, 2019, in response to misinformation about measles and its vaccines, and was expanded to account for the diffusion of COVID-19 related misinformation, on Jan 29, 2020. Therefore, our treatment group comprises both the tweets containing the trigger words of measles and vaccines and the tweets containing trigger words of the topics of COVID-19 that were posted after the expansion of the initial policy. The control group comprises the tweets that only contain words of other health topics and the tweets that contain COVID-19 related trigger words but that were posted before the corresponding launch of the policy.

4.3.2 The Effect of Twitter's Policy on Information Diffusion

We first employed the DiD model on our full dataset to estimate the effect of Twitter's policy on the diffusion of information on Twitter, regardless of truthfulness. The model for estimating the main effect on cascades is specified as follows:

$$\begin{aligned} Outcome_{it} = {} & \beta_1 Treat_i + \beta_2 After_t + \beta_3 (Treat_i \cdot After_t) + \beta_4 hashtags_i + \mathbf{Time_t} \\ & + \mathbf{Keyword_i} + \varepsilon_{it} \end{aligned} \tag{4.1}$$

where $Outcome_{it}$ indicates each of the four cascade metrics provided by Twitter; that is, the number of retweets, likes, quotes, and replies, of tweet i posted at time t. $Treat_i$ is a dummy variable that equals 1 (0) if tweet i belongs to the treatment (control) group. As mentioned above, if tweet i contains keywords related to COVID-19 and was posted after Jan 29, 2020, or if it contains keywords related to measles and vaccines, it is classified as the treatment group. Otherwise, it belongs to the control group. $After_t$ equals 1 (0) if time t was after (before) the initial launch of the policy (i.e., May 10, 2019). $(Treat_i \cdot After_t)$ is the treatment status indicator, which equals 1 if tweet i was affected by the treatment when it was posted, and equals 0 otherwise. Hence, the coefficient of interest to examine the effect of the new countermeasure on the spread of information is β_3.

Table 4.1: Main Effect of Twitter's Policy[1]

	Number of Retweets	Number of Replies	Number of Likes	Number of Quotes
Variable				
$Treat_i \cdot After_t$	-0.291***	-0.217***	-0.318***	-0.166***
	(0.052)	(0.039)	(0.064)	(0.030)
Year&Month FE	✓	✓	✓	✓
Keyword FE	✓	✓	✓	✓
Num of Obs	11,694	11,694	11,694	11,694

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[1] *Given the right-skewed distributions of all four cascade metrics, we did a log-transformation on the variables.*

$Hashtags_i$ is a dummy variable that indicates whether tweet i contains Twitter hashtags that may impact the cascade outcomes. In addition, we incorporated the keyword fixed effects $Keyword_i$, the tweet publication month and year fixed effects $Time_t$ to capture other factors that may affect the cascade results. The keyword fixed effects account for the differences of resulting cascade metrics across different topics. For example, tweets about COVID-19 may naturally grasp more attention than other tweets about cancer, which leads to a larger cascade. The tweet publication month and year fixed effects capture time-related variations. For example, the tweets that were posted earlier may had more time to attract readers and to be spread.

As shown in Table 4.1, the implementation of Twitter's policy results in a 29.1% (*p-value* $<$ 0.001) reduction in the number of retweets, a 21.7% (*p-value* $<$ 0.001) reduction in the number of replies, an 31.8% (*p-value* $<$ 0.001) reduction in the number of likes, and a 16.6% (*p-value* $<$ 0.001) reduction in the number of quotes. The results imply that Twitter's new misinformation countermeasure suppresses the cascades of information in all dimensions, regardless of truthfulness.

4.3.3 Heterogeneity in Treatment Effect across Tweet Truthfulness

As we explain in section 2, the impact of Twitter's policy may vary depending on the truthfulness of the tweets. To understand the holistic impact of the countermeasure, we empirically estimate

Table 4.2: Heterogeneous Treatment Effects across Tweet Truthfulness[1]

	Number of Retweets	Number of Replies	Number of Likes	Number of Quotes
Variable				
$Treat_i$ ·After$_t$ ·True$_i$	-0.240**	-0.156*	-0.246*	-0.102
	(0.113)	(0.084)	(0.136)	(0.065)
$Treat_i$ ·After$_t$ ·False$_i$	-0.233***	-0.179***	-0.253***	-0.139***
	(0.073)	(0.053)	(0.088)	(0.041)
Year&Month FE	✓	✓	✓	✓
Keyword FE	✓	✓	✓	✓
Num of Obs	11,694	11,694	11,694	11,694

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[1] *Given the right-skewed distributions of all four cascade metrics, we did a log-transformation on the variables.*

the moderating effect of truthfulness on the cascade metrics in Model 4.2.

$$\begin{aligned} Outcome_{it} = \beta_1 Treat_i + \beta_2 After_t + \beta_{31}(Treat_i \cdot After_t \cdot I[True_i]) \\ + \beta_{32}(Treat_i \cdot After_t \cdot I[False_i]) + \beta_4 hashtags_i \\ + \mathbf{Time_t} + \mathbf{Keyword_i} + \varepsilon_{it} \end{aligned} \tag{4.2}$$

where $I[True_i]$ is an indicator variable that equals 1 if tweet i is rated as True. $I[False_i]$ equals 1 if tweet i is rated as False. The parameter β_3s are the estimators capturing the moderating effects. The results are presented in Table 4.2.

The results suggest that the impacts of the adoption of Twitter's policy on information are negative for both true and false information diffusion, indicating that the policy suppresses the spread of both true and false information. Although the suppressive effect of the policy is stronger for false information in the number of replies, likes, and quotes (23.3% fewer retweets, 17.9% fewer replies, 25.3% fewer likes, 13.9% fewer quotes, *p-value* < 0.001), the spread of true information is also significantly suppressed (24.0% fewer retweets, 15.6% fewer replies, 24.6% fewer likes, *p-value* < 0.05; the effect of the policy on the number of quotes of true tweets is insignificant). These results suggest that, surprisingly, Twitter's misinformation policy not only effectively suppresses the spread of false information, but also exhibits a spillover suppressive effect on the spread of true information. To better understand the source of a such suppression effect on true information cascades, we explore the underlying mechanisms of how Twitter's policy affects the diffusion of information, in the following section.

4.3.4 Underlying Mechanism: People's Belief

In this section, we examine why Twitter's policy also suppresses the diffusion of true information. As discussed in Section 2.2.2, prior research (Pennycook et al. 2020b, Roozenbeek et al. 2021) has shown that an accuracy reminder may nudge people to consider the accuracy of new information when deciding whether to share it. If so, Twitter's policy may nudge users to focus more on the accuracy of the searched tweets when making sharing decisions. Then, they may be more likely to share the information that they believe is accurate and less likely to share information that they believe is inaccurate. Based on this reasoning, it is plausible that true information is suppressed because people do not believe true information as true. To explore this possibility, we collected additional data capturing potential discrepancy between people's belief and actual information truthfulness. Then, we introduced and estimated a DiD model to empirically inspect whether people's belief affects the extent to which Twitter's policy influences the diffusion of true and false information.

Measuring People's Belief

Regardless of the actual truthfulness, people may have their own belief about information. To capture how much people believe about public health information and investigate whether a discrepancy exists between the actual truthfulness and people's belief, we utilized Amazon Mechanical Turk (AMT), a crowd-sourcing platform for human intelligence tasks. Specifically, for each of the 852 health-related claims in our sample, we asked five independent MTurkers (i.e., participants) to rate the truthfulness of the claim based on their own judgment on a 1-5 scale, where 1 is "False," 2 is "Mostly False," 3 is "Unsure," 4 is "Mostly True," and 5 is "True." To avoid introducing confounding factors such as external information, we provided clear guidance to MTurks, in which we required them to rate the truthfulness of the claims without searching online or conferring with others. Figure 4.3 shows an example task shown to an MTurker. Each claim was then rated by five

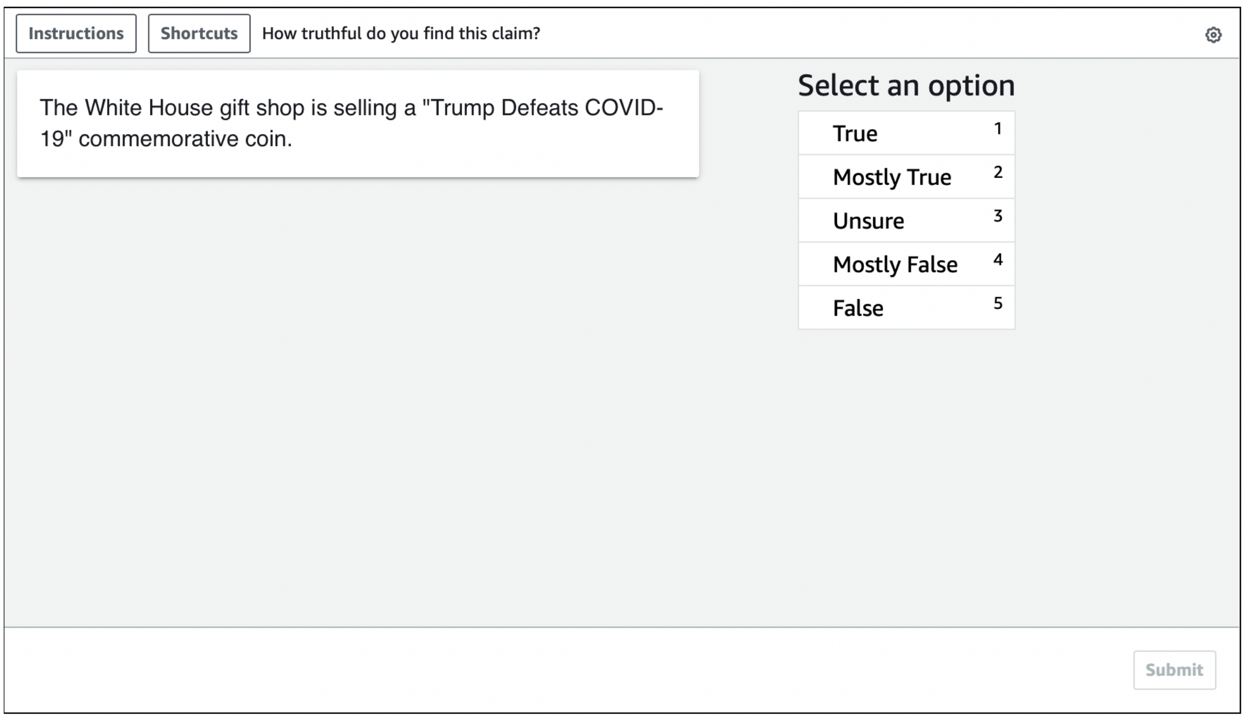

Figure 4.3: Example Task of MTurk

independent MTurkers. Finally, we calculated the average rating of the five MTurkers on every claim as a proxy of people's perceived truthfulness in the claim.

Discrepancy between People's Belief and Actual Truthfulness

To inspect whether people are able to identify the truthfulness of the claims about public health, we first show the distribution of MTurkers' average ratings of the true and false calims in Figure 4.4.

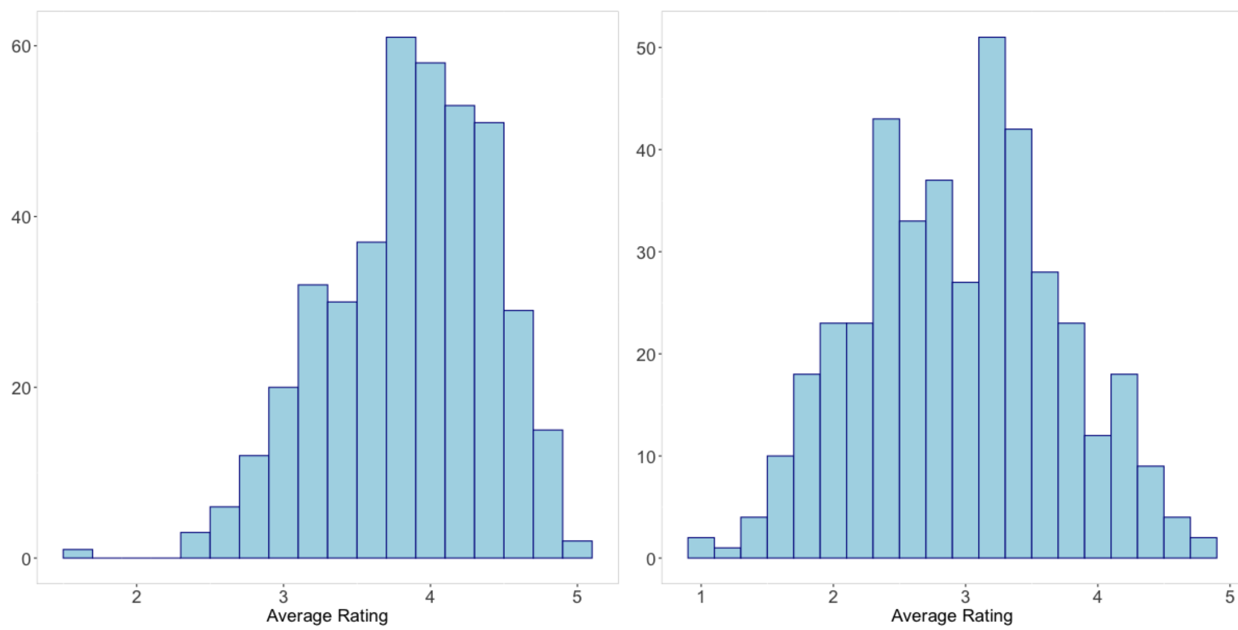

Figure 4.4: Distribution of people's belief in A) true claims; B) false claims.

The figures indicate that people have diverse beliefs about claims regarding public health topics and some are incapable of identifying the truthfulness of the claims, regardless of the actual truthfulness. We implemented a one-sample t-test to compare people's belief and the actual truthfulness of the claims. Our results show that the p-values of the test statistics are both smaller than 0.001, which indicates that people's beliefs of both true and false claims are significantly different from their actual truthfulness. The results indicate that people on average are unable to accurately discern the actual truthfulness of the information in health-related topics.

Table 4.3: Moderation Analysis: People's Belief[1]

	Number of Retweets	Number of Replies	Number of Likes	Number of Quotes
Variable				
$Treat_i \cdot \text{After}_t \cdot \text{True}_i \cdot \text{Rating}_i$	0.056*	0.050**	0.118***	0.127
	(0.033)	(0.024)	(0.040)	(0.019)
$Treat_i \cdot \text{After}_t \cdot \text{False}_i \cdot \text{Rating}_i$	0.057***	0.049***	0.100***	0.019
	(0.022)	(0.016)	(0.025)	(0.012)
Year&Month FE	✓	✓	✓	✓
Keyword FE	✓	✓	✓	✓
Num of Obs	11,694	11,694	11,694	11,694

[1] *Significance level:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

[1] *Given the right-skewed distributions of all four cascade metrics, we did a log-transformation on the variables.*

Interplay between People's Belief and Twitter's Policy

In this section, we empirically examine the moderating effect of people's belief on how Twitter's policy affects the diffusion of true and false information in Model 4.3.

$$\begin{aligned}Outcome_{it} = &\beta_1 Treat_i + \beta_2 After_t + \beta_{31}(Treat_i \cdot After_t \cdot I[True_i] \cdot Rating_i) \\ &+ \beta_{32}(Treat_i \cdot After_t \cdot I[False_i] \cdot Rating_i) + \beta_4 hashtags_i \\ &+ \mathbf{Time_t} + \mathbf{Keyword_i} + \varepsilon_{it}\end{aligned} \tag{4.3}$$

where $I[True_i]$ is an indicator variable that equals 1 if tweet i is rated as True. $I[False_i]$ equals 1 if tweet i is rated as False. $Rating_i$ is the proxy of people's belief in tweet i, which is measured by the average rating of the five independent MTurkers on the claim associated with tweet i. The parameter β_3s are the DiD estimator capturing the moderating effects. The results are presented in Table 4.3.

According to the results, the moderating effects of people's belief on the effects of Twitter's policy on the spread of true and false tweets are both positive. That is, if people believe a claim as true, the suppressive impact of the policy is significantly reduced. Specifically, people's belief significantly moderates the impacts of the policy on the retweeting, replying, liking, and sharing behaviours of true tweets ($\beta_{true,retweets} = 0.056$, *p-value* < 0.05; $\beta_{true,replies} = 0.050$, *p-value* < 0.05; $\beta_{true,likes} = 0.118$, *p-value* < 0.001). False tweets with a higher belief rating are also significantly less suppressed by the policy in the retweet number ($\beta_{false,retweets} = 0.057$, *p-value* < 0.05), reply number ($\beta_{false,replies} = 0.049$, *p-value* < 0.001), and like number ($\beta_{false,likes} = 0.100$, *p-value* < 0.001).

The results are consistent with our expectation. Twitter's policy nudges people to focus on the accuracy of the new information they receive when deciding whether to share it; and therefore, they tend to spread the tweets that they believe to be more accurate. However, according to the results we presented in Section 4.3.4, people are unable to accurately discern the actual truthfulness of health-related information, which leads to an undesirable suppression in their share of true tweets after the launch of Twitter's misinformation policy.

4.3.5 Treatment Effect on Authoritative Tweets

Based on the underlying mechanisms we explored, the spread of true information on Twitter might benefit from the assistance of the platform in helping users discern truths and falsehoods. Although Twitter has not offered any explicit truthfulness signals or indicators of each tweets, their verification of *authoritative* accounts may provide users with a signal of trustworthy information. To check if verification helps people discern truthfulness of claims, in this section, we examine how Twitter's policy affects the spread of the tweets posted by these authoritative accounts. Authoritative public health organizations such as World Health Organization and Centers for Disease Control and Prevention post tweets to share reliable information with users. We collected and randomly sampled 1,000 health-related tweets posted by these authoritative accounts, which had been verified by Twitter to be trustworthy and inspected the effect of Twitter's intervention on them by estimating the DiD model specified in Equation 4.1.

The results of this analysis is reported in Table 4.4. The results reveal that contrary to the true tweets posted by non-authoritative accounts (which are shown to be suppressed by Twitter's policy), the tweets posted by the authoritative accounts diffused even more after the policy implementation, in all four cascade metrics. The results indicate that, with the difficulty of distinguishing the truthfulness of the tweets, people may put more weight on the identity of the accounts posting the tweets; that is, whether the associated accounts are authoritative plays an important role in helping people determine whether the tweets are trustworthy to be spread. Therefore, people tend

Table 4.4: Effect of Twitter's Policy on Authoritative Tweets[1]

	Number of Retweets	Number of Replies	Number of Likes	Number of Quotes
Variable				
$Treat_i \cdot After_t$	2.265***	1.066**	2.384***	0.833**
	(0.482)	(0.421)	(0.496)	(0.402)
Year&Month FE	✓	✓	✓	✓
Keyword FE	✓	✓	✓	✓
Num of Obs	1,000	1,000	1,000	1,000

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[1] *Given the right-skewed distributions of all four cascade metrics, we did a log-transformation on the variables.*

to share tweets posted by the authoritative accounts more after the launch of Twitter's policy.

4.3.6 Relationship between People's Belief and Tweet Characteristics

The previous sections demonstrate the important role of people's beliefs in moderating how Twitter's policy affects the cascades of true and false information. In this section, we explored the correlations between the characteristics of the tweets and the extent to which people believed them to be true. Although this is a correlational analysis, it can help provide potential guidance to users and the platform. To this end, we utilize the model shown in Equation 4.4.

$$Rating_i = \gamma_1 \cdot TweetLen_i + \gamma_2 \cdot Sentiment_i + \gamma_3 \cdot FollowerNum_i + \gamma_4 \cdot Verified_i + \varepsilon_i \tag{4.4}$$

where $TweetLen_i$ indicates the length of tweet i, $Sentiment_i$ indicates the sentiment score of tweet i, $FollowerNum_i$ indicates the number of the followers of the account which owns tweet i, and $Verified_i$ is a dummy variable that equals 1 (0) if the account posting tweet i is verified (unverified) by Twitter.

First, the previous literature has suggested that a high-quality message that users can fluently process may be perceived as a signal of truth (Unkelbach 2007). Relatedly, the prior literature found that the text length has a positive effect on the perceived text quality (Guo et al. 2013). We, therefore, used the length of the tweet as a proxy to measure how well the tweet is encoded and explored its relationship with people's beliefs. As shown in Model 1 of Table 4.5, a significant positive relationship exists between the tweet length and people's beliefs. A longer tweet may indicate a higher quality of the content and may positively signal the information's truthfulness.

Second, it has been shown that by drawing more attention, a negative message may be perceived as more valid (Hilbig 2011). We applied a pre-trained naive Bayes classifier to obtain the sentiment scores of the tweets to measure their valence and added this proxy to the previous model. The result is reported in Model 2 of Table 4.5. The sentiment score exhibits a significant negative correlation with people's belief in the tweet, which indicates that a tweet comprising more negative content may be associated with greater validity.

Third, the previous literature has demonstrated that information published by a more trustworthy source leads to a higher belief of receivers(Kim et al. 2019, Ecker et al. 2022). Accordingly, we used the number of followers of an account as a proxy. A massive number of followers could be an authoritative signal for an account. We then included this measure in the model. As shown in Model 3 of Table 4.5, the number of account followers has significant and positive correlations with people's belief in the tweet. An account having more followers may be perceived to be more trustworthy, which may be positively associated with the perceived truthfulness of its tweets.

Last but not least, other than the number of account followers, the account's verification status (provided by Twitter) can also serve as a proxy for its credibility rating. An account verified by Twitter is required to be authentic, notable, and active[7], and therefore may generate a positive signal in its believability. We then incorporated the account verification status into the model. The result is shown in Model 4 of Table 4.5. A tweet posted by an account verified by Twitter significantly positively correlates with people's belief in it. Notably, after including the account verification status in the model, the correlation between the account follower number and people's beliefs becomes insignificant, implying that the verification status provides a stronger signal of the account credentials.

Furthermore, we explored the heterogeneous relationships between the tweet characteristics and people's belief across tweet truthfulness. The results are shown in Table 4.6. We find a consis-

[7]https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts

Table 4.5: Relationship between People's Belief and Tweet Characteristics[1]

	Model 1	Model 2	Model 3	Model 4
Variable				
TweetLen	0.443***	0.421***	0.363***	0.317***
	(0.019)	(0.018)	(0.019)	(0.018)
Sentiment		-0.290***	-0.291***	-0.308***
		(0.019)	(0.019)	(0.018)
FollowerNum			0.052***	0.004
			(0.003)	(0.004)
Verified				0.919***
				(0.035)
Num of Obs	11,694	11,694	11,694	11,694

1 *Significance level:* * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
2 *To account for the skewed distribution of the tweet length and the number of follower of tweet posters, we applied a log-transformation during the estimation process.*

tent correlation relationship across tweets with true and false claims.

4.4 Robustness Checks

We ran a battery of robustness checks to further validate our results and check their robustness. First, in our data, tweets are nested within claims. Tweets that belong to the same claim may exhibit specific diffusion patterns. To account for such unobserved heterogeneity, we incorporate the claim random effects in our DiD model to examine the main effect. We choose to employ the random effects instead of fixed effects due to the relative short time window of the tweets nested within each claim in our dataset. That is, for each claim, the matched tweets were all posted within seven days; therefore, the treatment effects of Twitter's policy would be completely absorbed if we include the claim fixed effects. Hence, we add the claim random effects instead, to control for unobserved heterogeneity introduced by different claims, and incorporated the keyword fixed effects to account for possible endogeneity concerns caused by different topics. As shown in Table 4.7, the result is qualitatively consistent with our main result.

Second, the validity of a DiD model relies on an assumption of parallel trend. That is, the treatment and control groups should have common trends in their cascades in the periods prior to the treatment (Agrawal and Goldfarb 2008). Following the previous literature (Angrist and Pischke

Table 4.6: Relationship between People's Belief and Tweet Characteristics across Truthfulness[1]

	True	**False**
Variable		
TweetLen	0.377***	0.298***
	(0.0.040)	(0.025)
Sentiment	-0.323***	-0.324***
	(0.040)	(0.025)
FollowerNum	0.006	0.000
	(0.008)	(0.005)
Verified	0.928***	0.915***
	(0.076)	(0.048)
Num of Obs	11,694	11,694

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[2] *To account for the skewed distribution of the tweet length and the number of follower of tweet posters, we applied a log-transformation during the estimation process.*

Table 4.7: DiD Analysis: with Claim Random Effects[1]

	Number of Retweets	**Number of Replies**	**Number of Likes**	**Number of Quotes**
Variable				
$Treat_i \cdot After_i$	-0.091*	-0.082**	-0.122*	-0.050*
	(0.052)	(0.037)	(0.063)	(0.029)
Year&Month FE	✓	✓	✓	✓
Keyword FE	✓	✓	✓	✓
Num of Obs	11,694	11,694	11,694	11,694

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[1] *Given the right-skewed distributions of all four cascade metrics, we did a log-transformation on the variables.*

2008), we implemented a relative time model that incorporated the pre-treatment periods. Specifically, we decomposed the periods prior to the launch of Twitter's policy into a series of dummies, denoted by $Pre_{it}(j)$, and estimated their associated coefficients in the same DiD setting to examine whether the treatment effects was present before Twitter's intervention, as shown below:

$$Outcome_{it} = \sum_j \eta_j (Treat_i \cdot Pre_{it}(j)) + \beta_1 Treat_i + \beta_2 After_t + \beta_3 (Treat_i \cdot After_t) + \beta_4 hashtags_i + \mathbf{Time_t} + \mathbf{Keyword_i} + \varepsilon_{it} \tag{4.5}$$

where $Pre_{it}(j)$ is an indicator that equals 1 if period t is j months prior to the launch of Twitter's policy. The parameter η_js, therefore, captures the effects of the pre-treatment periods.

We set one month prior to Twitter's intervention as the reference period and consider a six-month periods prior to it (Angrist and Pischke 2008). Figure 4.5 shows the estimates of the pre-treatment coefficients η_js with the outcome variable measuring the number of retweets, replies, likes, and quotes, respectively. As can be seen, all η_js are statistically insignificantly different from zero, which indicates that our estimated treatment effect is not driven by differential trends before Twitter's policy.

Third, we implemented a placebo test through a random treatment analysis to address the concern regarding possible false significance caused by serial correlation in the dependent variable (Bertrand et al. 2004). Such concern arises from the dependence of the estimation of difference-in-differences models on time series data, addressing that the dependent variables may be positively serially correlated. Following the previous literature (Burtch et al. 2018), we randomly shuffled and reassigned the treatment indicators to the tweets in our sample. With the shuffled data, we then re-estimated our main DiD model. We replicated this procedure 1,000 times and stored the estimations. If our model doesn't suffer from the serial correlation problem, the mean of the estimation results should be insignificant.

As shown in Figure 4.6, the distributions of the estimated coefficients of the pseudo shuffled treatment indicators for the four outcome variables are all centered at zero. The results indicate

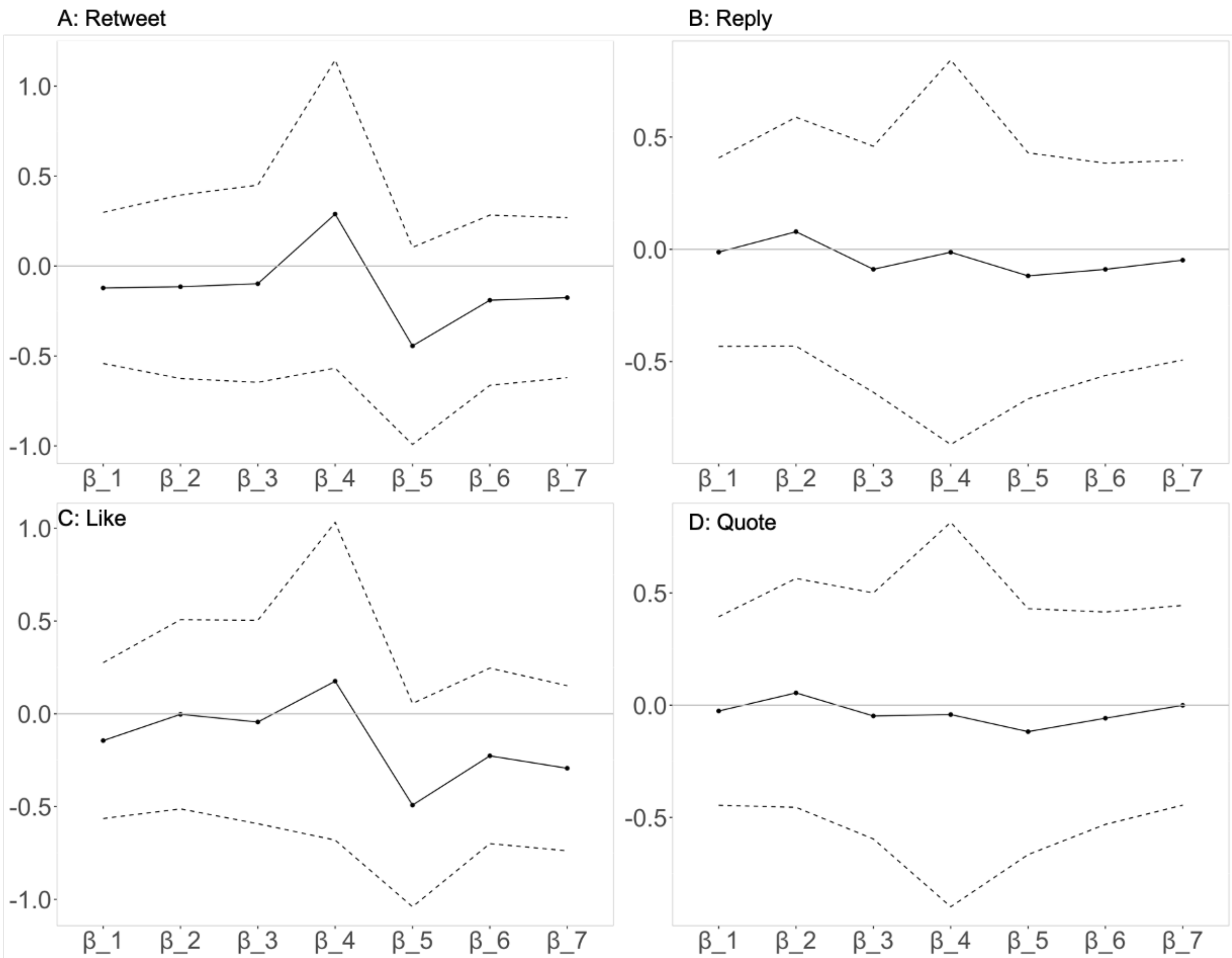

Figure 4.5: Difference-in-Difference Coefficients Before Twitter's Policy. A) Number of retweets; (B) Number of replies; (C) Number of likes; (D) Number of Quotes

Note: the solid line depicts the estimated coefficients, and the dashed lines depicts a 95% confidence interval of the coefficients.

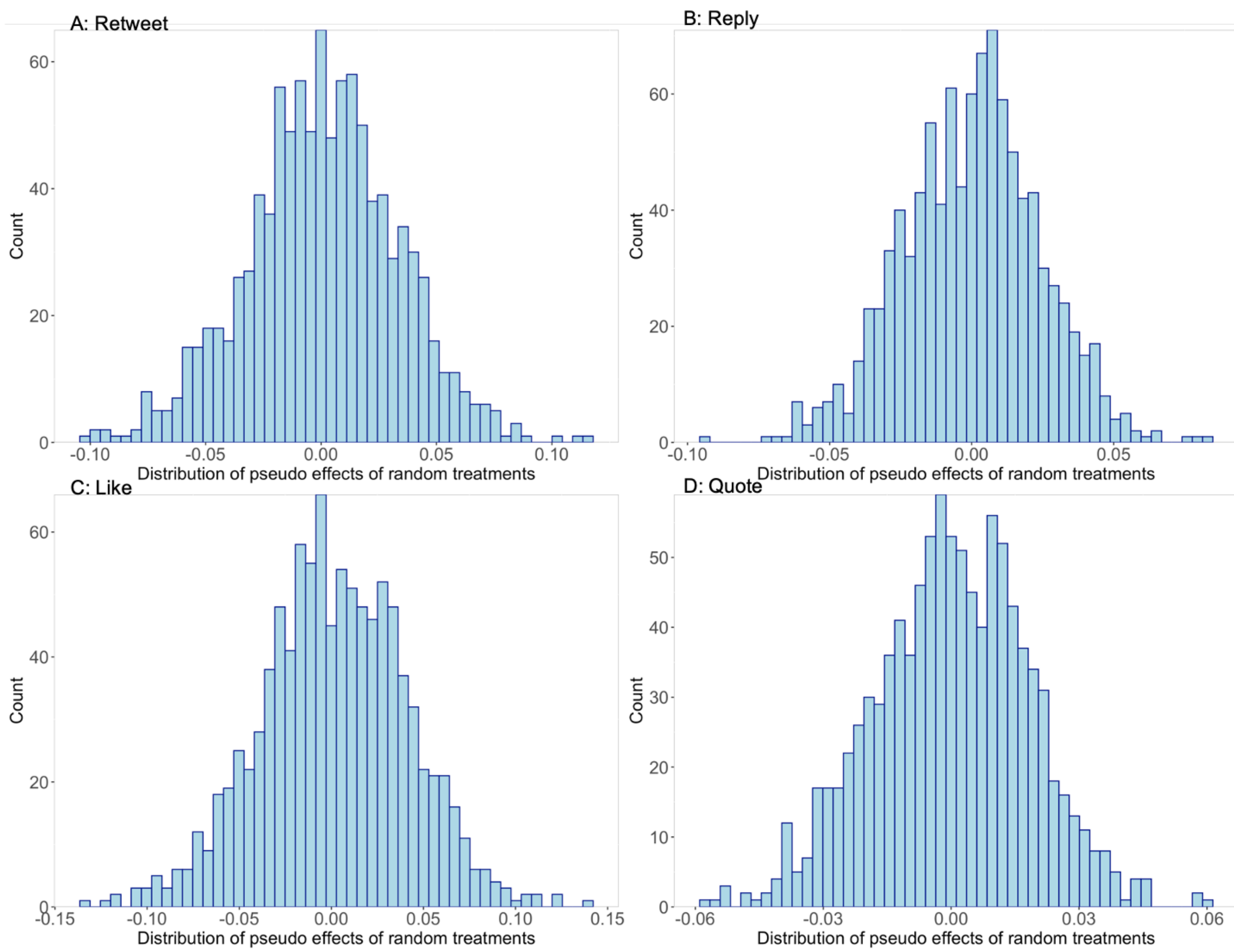

Figure 4.6: Shuffled Treatment Test: Distribution of Pseudo Effects A) Number of retweets; (B) Number of replies; (C) Number of likes; (D) Number of Quotes

that we can reject the hypothesis that the estimated effects of Twitter's policy on the cascades of tweets were driven by the serial correlation in the cascade measures, with a 95% confidence level.

4.5 Conclusion

Ranging from suspicious or harmful remedies to conspiracy theories, the rapid spread of misinformation on public health has become a global problem. To combat this "infodemic," social platforms employ countermeasures aiming to suppress the spread of misinformation. The previous literature has studied whether various countermeasures effectively decrease misinformation cascades. However, whether and how the spread of true information is affected by the misinformation policy remains unclear. In this study, we focus on one such intervention implemented by Twitter, initiated in May 2019, to inspect the impact of Twitter's policy on the spread of true information, comparing it with that of falsehoods.

Our analysis reveals that, other than inhibiting misinformation, Twitter's policy also unintentionally suppresses the spread of true information. Since the introduction of the intervention, all public health-related tweets are less spread, regardless of the truthfulness. Although the suppressive effect of the policy is comparably stronger for false information, the spread of true information in terms of the number of retweets, replies, and likes is also suppressed. We found that, due to difficulty in discerning the actual truthfulness of public health information, people's share of true information decreases after the launch of the policy. Contrary to the tweets posted by common non-authoritative accounts, we further found that the tweets posted by accounts that are verified as authoritative in public health spread even more since the launch of Twitter's policy. The results suggest that, incapable of distinguishing the truthfulness of the tweets, people put more weight on the identity of the accounts posting the tweets after the intervention, and tend to share more of the tweets posted by the authoritative accounts. Lastly, through an inspection of the correlations between various characteristics of tweets and people's belief in them, we find that people's perceived truthfulness of a tweet is positively correlated with its textual length and the verification status of its poster but negatively correlated with its valence.

Our findings have several contributions. First, to our best knowledge, no previous study has empirically examined the impact of the actual misinformation countermeasure implemented by a social media platform on true information. Chiou and Tucker (2018) studied whether and how Facebook's ban on advertising fake news sites affected the spread of falsehoods, and Hwang and Lee (2021) examined the effect of Twitter's search prompt intervention on the spread of false articles. Our study, meanwhile, provides the first evidence that the misinformation policy, which serves as a pre-warning, has an undesirable suppressive effect on the spread of true information as well as on the spread of falsehoods.

Second, our findings contribute to the literature that studies how misinformation is spread. Previous literature revealed that with unattractive topics which are unaligned with the receiver's interest, misinformation could be easily accepted by people due to a lack of motivation to question its validity (Schul et al. 2008). Pennycook et al. (2020a) also suggested that people's intention could be shifted to other aspects of the information, such as partisanship, rather than its truthfulness when facing political misinformation. Our study complements previous literature by exploring how public health-related misinformation is spread, in which the diffusion is partly attributable to people's incapability to accurately discern the actual truthfulness of the information.

Third, our study also sheds light on how account identity affects the effects of misinformation policy. The previous literature has shown that the source credibility plays an essential role in helping people form their belief in a piece of new information (Ecker et al. 2022). Kim et al. (2019) reported that information published by a more trustworthy source is perceived to be more credible by the receivers. Through inspecting the effect of Twitter's policy on a set of accounts that are verified as authoritative to the public, our findings provide empirical evidence that the identity of the accounts publishing the information facilitates discernment about the actual truthfulness of the information; that is, people tend to share more information posted by authoritative accounts since the launch of the misinformation policy.

Our findings provide several managerial implications. To combat the rapid spread of misinformation, social platforms have implemented various countermeasures. However, while such interventions may effectively suppress misinformation cascades, an unintentional suppressive effect on the spread of true information may also be incurred. Our results suggest that the pre-warning misinformation policy such as that implemented by Twitter does just that. Based on our findings, platforms need to be alerted and might want to intervene in a more cautious way so that the cascade of truth is protected from the falsehoods. Furthermore, our analysis reveals that despite being nudged to focus on information truthfulness by the misinformation policy, people still have difficulty distinguishing the actual truthfulness; given this difficulty, platforms could consider how to help people discern true and false information, especially in the fields that require expertise, such as public health. For example, it might be worthwhile to encourage users who own an authoritative or verified account to post reliable information in longer text, which, according to our correlational analysis, has a positive correlation with people's perceived truthfulness of the information.

Chapter 5

URGENT VS. NON-URGENT INQUIRIES: AN EMPIRICAL STUDY OF ENGAGING VOLUNTARY CONTRIBUTIONS IN ONLINE COMMUNITIES

5.1 Introduction

Serving as a convenient channel for people to connect and collaborate, online communities have emerged to play an important role in facilitating knowledge-sharing and problem-solving (Goh et al. 2016, Ma and Agarwal 2007). Fueled by Web 2.0, an online community gathers a massive population of individuals who are geographically diverse but share a common interest, activity, or identity (Faraj et al. 2016). One prominent example is community-based Question-and-Answer (Q&A) websites where people can ask, answer, and discuss questions, such as StackExchange and Quora. Bringing together the wisdom of a community with mutual interest or practice, open questions posted on Q&A platforms are usually solved efficiently with a quick turnaround rate which is hard for search engines to beat (Khansa et al. 2015, Lou et al. 2013). Previous researchers have been focusing on investigating individuals' online engagement behaviors on Q&A websites. For example, Wang et al. (2013) segmented users in Stackoverflow into questioners and answerers and examined the difference between their engagement frequencies. Khurana et al. (2019) focused on a Q&A site connecting doctors and patients and investigated the role expertise plays in answering behaviors. In a study of StackExchange, Chen et al. (2017) explored the motivations of users to contribute answers from a dynamic point of view.

However, prior studies have rarely explored the difference in individuals' engagement behaviors in response to various types of questions. While questions posted on Q&A websites are generally initiated by a common interest or identity shared by the associated community, still they may possess different attributes. For example, on corporate knowledge-sharing platforms, hierarchy would be an essential factor affecting individuals' participation as employees are disinclined to share their knowledge with their higher-ups (e.g, avoid answering questions posted by their managers) (Meske et al. 2020, Pu et al. 2022). The rank of questioners in the community is not the only property that may affect individuals' responding behaviors to the questions. For the communities gathering individuals sharing a mutual practice that involves safety or health concerns, such as the freight driver community and the doctor-patient community, some associated online Q&A platforms start to employ a question-labeling feature, which enables users to report the time-urgency level when posting a new question. In these communities, such an urgency level not only reveals the extent to which the individual is eager to solve the problem but also implies the questioner's exposure to potential risks if the question fails to be solved promptly. Thus, it is essential to investigate users' responding behaviors to questions with different urgency levels and underlying motivations.

As the core part of a Q&A platform is maintained by participants' contributions which are usually voluntary without any monetary compensation, it is critical for the platforms to sustain users' motivations to contribute their knowledge (Gazan 2011, Zhao et al. 2016). Most of the online communities suffer from a declining user contribution rate over time (Simonite 2013), including Q&A sites. To engage user contributions in such a setting, a variety of information technology (IT) artifacts have been designed and applied by online platforms, such as recognition systems, helpfulness verification, and badges (Ray et al. 2014, Zichermann and Cunningham 2011). However, these extrinsic motivation mechanisms may not always function as expected. For example, Garnefeld et al. (2012) found that explicit monetary incentives may negatively affect individuals' long-term posting behaviors in an online community. While the external reward is intentionally implemented to motivate individuals' engagement, they may perceive it as a lack of acknowledgment of their internal interest and involvement (Frey and Jegen 2001), thus less motivated to make contributions on the platform. Moreover, the effect of the motivation mechanisms may not be static and consistent across active and inactive users, which calls for an investigation into the dynamics of these IT artifacts (Chen et al. 2017).

The prior literature on exploring how various motivation mechanisms would shape individuals' engagement behaviors when facing different types of questions in a Q&A community, however, is limited. In light of this gap, in this paper, we focus on investigating individuals' reactions to questions with different time-urgency levels and unveiling the underlying motivations. We collected data from a leading online freight-driver Q&A platform in China. Bringing together more than three million drivers from around 300 cities, the platform provides a channel where the drivers can post and answer questions they met on the road. To better accommodate the wide range of questions from the inquiry about the highway tolling charge to seeking advice during a car accident, the platform implements a question-labeling feature. Specifically, when posting a new question, the driver is asked to indicate whether their question is time urgent or not. Such an urgency-level indicator is then attached to the beginning of the question and is visible to other drivers on the platform. In addition, a variety of motivation mechanisms are also adopted to engage drivers' participation. For instance, *club* is one of the unique features supported by this platform, which allows drivers located in the same province to form a small group inside the community with a private group chat channel.

To investigate how various IT artifacts adopted by the platform engage individuals' responding behaviors across questions with different time-urgency levels, we took a dynamic approach. Specifically, we built a multi-dimensional Hidden Markov Model (HMM). The HMM framework explicitly models the structural dynamics of user contributions with different underlying latent motivation states, as well as the transition between the states. Utilizing this framework, we are then able to examine the heterogeneous effects of the motivation mechanisms on drivers' motivation levels. Moreover, different from previous literature assuming one-dimensional engagement behavior, we modeled drivers' responding behaviors to urgent and non-urgent questions as a multi-dimensional vector to capture multiple response dimensions simultaneously. We then calibrated our HMM model using the data collected from the aforementioned freight-driver Q&A platform.

Our findings are summarized as follows. To begin with, this study is one of the first works that scrutinize various aspects of personal behaviors in online Q&A platforms, specifically concerning the varying urgency levels of inquiries. The research empirically estimated the divergent impacts that individual and community attributes might have on users' responses to both urgent and non-urgent questions.

Moreover, this study enriches the literature on the possible social consequences of community size on individual participation. We dive into how the overall community size and the inherent sub-groups affect user contributions on Q&A platforms separately. Interestingly, we discover that while a larger main community tends to stimulate more contributions from the user, being part of a larger sub-group may diminish the perceived importance of their input, subsequently reducing their response activities.

Lastly, the HMM framework enables us to examine the evolution of users' motivational states and the effectiveness of the motivation strategies implemented by the platform. Contrary to expectations, our study reveals that as the volume of unresolved issues shared in a sub-group's chat channel increases, a user in a low motivation state is less likely to rise to a higher motivation state. These findings advise online Q&A platforms to be wary of the unexpected effects of creating sub-groups within the main community and recommend a more subtle approach than just indiscriminately sharing unsolved questions with sub-group members.

5.2 Empirical Framework

In this section, we introduce the empirical setting of our study and construct our model accordingly.

5.2.1 Research Context

As mentioned in Section 3.1, we collected the data for this study from a leading online community-based freight driver Q&A platform in China. The platform brings together over three million drivers based in around 300 cities nationwide. Drivers joining the forum can post any questions they met on the road as well as supply answers to other drivers' inquiries. A unique feature of such a freight-driver-oriented channel is the volatile time-urgency level of the questions posted. Unlike regular interest-driven Q&A sites such as StackOverflow and StackExchange where urgent questions are rare, some questions posted on this platform could reflect the risky safety condition of the questioner (e.g., in a car accident, etc.) and therefore possess a higher time-urgency level.

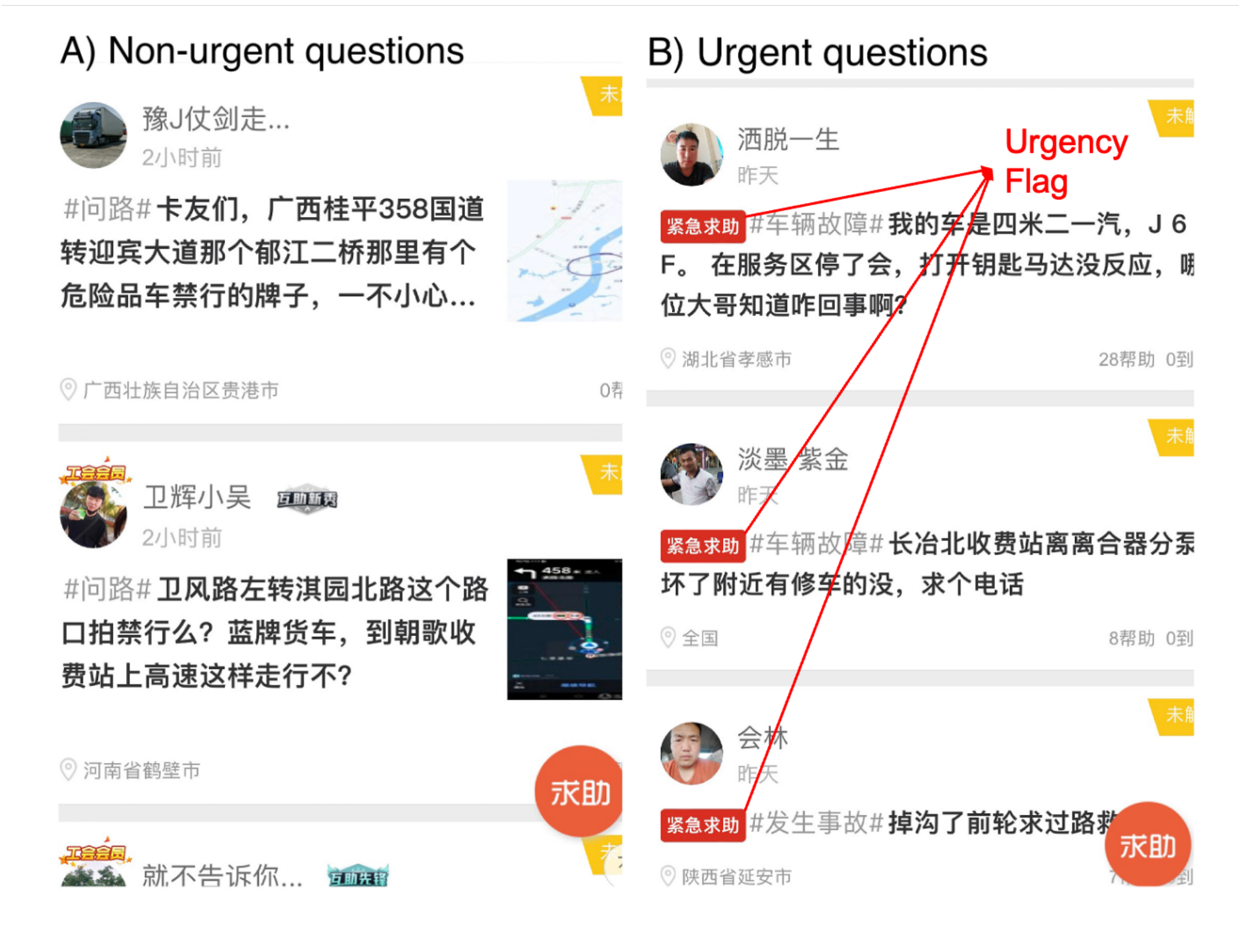

Figure 5.1: Examples of (a) non-urgent questions (b) urgent questions attached with an urgency flag.

To better accommodate this situation, the platform introduces a time-urgency labeling feature, enabling drivers to indicate whether their questions are urgent or not when posting them. If the question is rated as urgent, an urgency flag would be attached to the beginning of the question; otherwise, the question is posted with only the inquiry content. We illustrated this urgency labeling system in Figure 5.1. As a community-based Q&A forum, the platform relies heavily on user contribution. To motivate users' participation, several motivating mechanisms have been adopted. First, after posting a new question, the questioner would pick an answer from all the answers they receive and accept it as the solution to the question. The picked answer is then labeled as *effective help* and pinned to the top of the list of answers. Second, the platform would review the solved questions (i.e., questions with effective help) on a weekly basis, screen out the most widely-concerned questions, and recognize the users who provide effective solutions to the questions. Last, considering the importance of geographic locations to freight drivers, the platform allows users based in the same provinces to form sub-groups within the large community. The sub-groups, known as the *clubs*, have private group chat channels in addition to the large forum. On a random basis, the platform would share unsolved inquiries to the clubs' chat channels.

5.2.2 Multi-Dimensional Hidden Markov Model

The evolving nature of user motivation and other explanatory factors may lead to the fluctuation in user contribution (Franzoni and Sauermann 2014). To capture such a dynamic process, we applied a Hidden Markov Model (HMM) framework which identifies the user's motivation as a latent state, moving across different motivation levels following a Markovian process. The HMM has been widely utilized in a variety of fields in previous literature, such as developers' learning dynamics in open source projects (Singh et al. 2011), mobile application usage (Wu et al. 2022), patients' mental health in online health community (Yan and Tan 2014), and ads consumption in mobile games (Deng et al. 2021). Taking a two-layer structure, the HMM framework is capable to model a hidden stochastic process which can be observed through the observations generated by another set of stochastic processes (MacDonald and Zucchini 1997). The HMM is hence suitable to our setting, as users' motivation states are not directly observable, but are reflected through another stochastic process leading to observable online activities (e.g., responding behaviors to urgent and non-urgent questions). Moreover, the HMM enables us to investigate the transition in users' motivation states across different stages as well as the effects of the underlying triggering factors.

We illustrate the multi-dimensional HMM framework established in our research context in Figure 5.2. Under this framework, the volumes of the user's responses to urgent and non-urgent questions construct the two-dimensional observable outcomes that are stochastically determined by their current hidden motivation states. Triggered by the motivating mechanisms implemented by

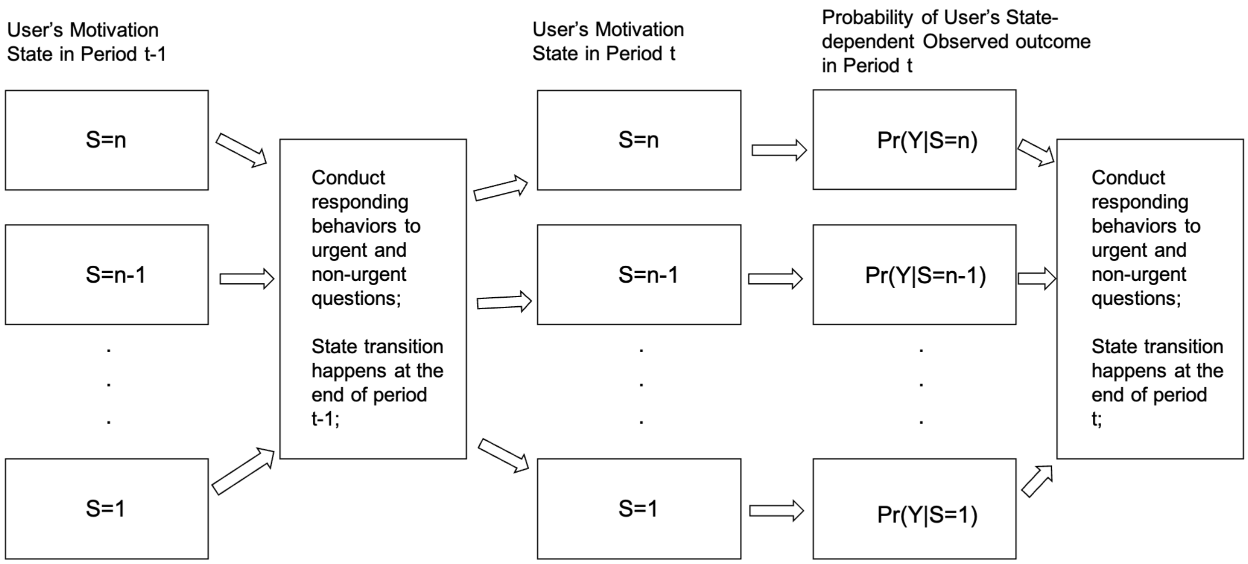

Figure 5.2: Hidden Markov Model of User's Motivation State Transition

the platform, the user's latent motivation states may switch across n different stages. In any period t, a user is in only one state. Our proposed HMM framework thus comprises three elements: the initial state distribution, π; the state-transition matrix, A; and the observed outcome distribution, P.

5.2.3 *State-Transition Matrix*

The state-transition matrix contains the probabilities with which a user's latent motivation state switches. Similar to other HMMs, we model the transitions in states as a Markov Process, assuming a total of n motivation stages where 1 denotes the lowest stage and n denotes the highest stage. From $t-1$ to t, affected by the communication with the community as well as other motivating artifacts, the user may switch to a different motivation state or stay idle if the incentive is not strong enough. We allow the user to jump from the lowest state to the highest state and vice versa, so as to capture their potential immediate gain or loss of motivation to contribute. For a user i in period t, we define their state transition probability as $a_{it}(s,m) = p(s_{it} = m|s_{it-1} = s), 1 \leq j,m \leq n$. For each state s, we have $\sum_{m=1}^{n} a_{it}(s,m) = 1$ and $0 \leq a_{it}(s,m) \leq 1$.

Following previous literature, a user can move to a higher motivation state if the benefit they receive is greater than a threshold, whereas they will switch to a lower state if the aggregated impact is lower than a low bound. Hence, we define the state transition matrix as an ordered logit model:

$$\begin{aligned}
a_{it}(s,n) &= 1 - \frac{exp(\bar{\omega}_{s\to n} - \beta_s X_{it})}{1+exp(\bar{\omega}_{s\to n} - \beta_s X_{it})} \\
a_{it}(s,n-1) &= \frac{exp(\bar{\omega}_{s\to n} - \beta_s X_{it})}{1+exp(\bar{\omega}_{s\to n} - \beta_s X_{it})} - \frac{exp(\bar{\omega}_{s\to n-1} - \beta_s X_{it})}{1+exp(\bar{\omega}_{s\to n-1} - \beta_s X_{it})} \\
&\dots \\
a_{it}(s,s) &= \frac{exp(\bar{\omega}_{s\to s+1} - \beta_s X_{it})}{1+exp(\bar{\omega}_{s\to s+1} - \beta_s X_{it})} - \frac{exp(\omega_{s\to s-1} - \beta_s X_{it})}{1+exp(\omega_{s\to s-1} - \beta_s X_{it})} \qquad (5.1) \\
&\dots \\
a_{it}(s,2) &= \frac{exp(\omega_{s\to 2} - \beta_s X_{it})}{1+exp(\omega_{s\to 2} - \beta_s X_{it})} - \frac{exp(\omega_{s\to 1} - \beta_s X_{it})}{1+exp(\omega_{s\to 1} - \beta_s X_{it})} \\
a_{it}(s,1) &= \frac{exp(\omega_{s\to 1} - \beta_s X_{it})}{1+exp(\omega_{s\to 1} - \beta_s X_{it})}
\end{aligned}$$

where s is the current state, $\omega_{s\to k}$ is the threshold for the current state to switch to a lower state $k(k<s)$, $\bar{\omega}_{s\to k}$ is the threshold for the current state to switch to a higher state $k(k>s)$. For each s, we restrict that $\bar{\omega}_{s\to n} \geq \bar{\omega}_{s\to n-1} \geq \cdots \bar{\omega}_{s\to s+1} \geq \bar{\omega}_{s\to s-1} \geq \cdots \geq \bar{\omega}_{s\to 1}$. X_{it} is a vector of variables affecting users' transition between states and β_s is a vector of corresponding state-dependent coefficients.

5.2.4 Multi-Dimensional State-Dependent Outcome

As mentioned in Section 5.2.2, we focus on the responding behavior of the user on the Q&A platform and thereby choose the number of responses provided by the user to urgent and non-urgent questions to construct a two-dimensional outcome variable. Given the user's state, the observed responding activities are assumed to be conditionally independent. Following previous literature (Yang et al. 2019), we assume the number of replies to questions of type k ($k=0$ indicates questions are non-urgent and $k=1$ indicates questions are time urgent), a count variable, to follow a negative binomial (NB) distribution for a given motivation state:

$$P(O_{ikt}|S_{it}=s)=\frac{\Gamma(\theta_s^{-2}+O_{ikt})(\theta_s^{-2})^{\theta_s^{-2}}exp(Y_{it}\gamma_{sk}+\eta_{ik})^{O_{ikt}}}{\Gamma(O_{ikt}+1)\Gamma(\theta_s^{-2})(exp(Y_{it}\gamma_{sk}+\eta_{ik})+\theta_s^{-2})^{\theta_s^{-2}+O_{ikt}}} \tag{5.2}$$

where O_{ikt} is the number of answers posted by user i at time period t in response to type k questions and θ_s is the state-dependent parameter to capture the potential over-dispersion in O_{ikt}. Y_{it} is the vector consisting of variables that have a direct impact on the outcome for user i at time period t and γ_s is a set of associated state-dependent parameters.

In addition, we use η_{ik} to denote the individual-level random effect of user i in dimension j (i.e, in response to type j of questions), which enables us to address potential unobserved individual heterogeneity. Furthermore, we are able to capture potential correlations among outcomes respecting different time-urgency levels rising from individual characteristics through modeling the joint distribution of user-specific random effects. Following Heckman and Singer (1984), we implemented a non-parametric method to estimate the joint distribution of random effects. Specifically, we first selected a fixed number of supports. The supporting points and corresponding probabilities were then estimated by optimizing the likelihood function.

5.2.5 Likelihood of an Outcome Sequence

We then combine the aforementioned elements to derive the likelihood function. For a user i, given an observed sequence of outcomes $O(i)=O_{i1}O_{i2}\cdots O_{iT}$ and a sequence of latent states $S(i)=S_{i1}S_{i2}\cdots S_{iT}$, the likelihood function conditional on the individual-level random effects is defined as below:

$$L(O(i)|\eta_i)=\sum_{s_1=1}^{n}\sum_{s_2=1}^{n}\cdots\sum_{s_T=1}^{n}P(S_{i1}=s_1)\prod_{t=2}^{T}P(S_{it}=s_t|S_{it-1}=s_{t-1})\prod_{t=1}^{T}P(O_{it}|S_{it}=s_t) \tag{5.3}$$

where $O_{it}=(O_{i0t},O_{i1t})$. $s_t\in\{1,...,n\}$ indicates the state a user can potentially land in at time period t and $P(S_{i1}=s_1)$ denotes the initial state distribution. Integrating over the random effects η_i, we derive the likelihood of user i as follows:

$$L(O(i)) = \int_{\eta_i} L(O_i) dG(\eta_i) \tag{5.4}$$

where $G(\eta_i)$ is the joint distribution of the random effects. Finally, the overall distribution of the population can be calculated as $L(O) = \prod_{i=1}^{N} L(O_i)$ where N denotes the sample size.

5.3 Data and Variable Constructions

The freight-driver Q&A platform provides us with a one-year sample including information on the questions posted on the forum, associated replies, and characteristics of the corresponding users. For model calibration, we chose to focus only on the users who make more than five contributions throughout the one-year sample period, as the identification of the underlying dynamic model from noise would be difficult with too many zeros in the data (Huang et al. 2019). Considering our limited computation capacity, we then aggregated the online activities of the users on a weekly basis across 54 weeks and randomly sampled 1,000 users of the whole population to form our final data used for estimation. Table 5.1 presents the variable sets and shows detailed summary statistics.

Individuals' motivation states are not observed. However, they are reflected by the corresponding responding activities, and thereby the latter can be utilized as the observed state-dependent outcome. As stated in the previous section, we calibrated the outcome variable to be a two-dimensional vector, capturing users' contributions to urgent and non-urgent questions simultaneously. As shown in the table, users on average contribute to more non-urgent questions than urgent questions, which is consistent with the unbalanced distribution of urgent versus non-urgent questions posted on the platform [1]

Apart from the state-dependent outcome, two sets of variables are constructed. The first set comprises variables affecting the state-transition matrix. First, if the questions posted by the user are answered by others in the community, they may be more inclined to return the favor through contributing more responses to other users' questions. In our context, such reciprocity is captured by the number of replies received to the user's past questions, denoted by $Help\_received_{it-1}$. Sec-

[1] On average, around 710 urgent questions and 1,610 non-urgent questions are posted to the community weekly.

Table 5.1: Summary Statistics of the Data

Variables	Mean	Standard Dev.	Min	Max
Responding Behavior				
$Help_{it,urgent}$	1.545	4.404	0	188
$Help_{it,non-urgent}$	3.275	8.763	0	346
Variables affecting State-Transition Matrix				
$Help\_received_{it-1}$	11.480	27.053	0	363
$Help\_effective_{it-1}$	30.430	66.033	0	843
Big_events_{it-1}	3.305	6.276	0	64
$Inquiries\_shared_{it-1}$	35.02	71.460	0	1,056
Variables affecting State-Dependent Outcome				
$Matched\_locs_{it}$	387.000	238.461	0	907
$Tenure_{it}$	730.100	355.503	0	1577
$Active\_users_{it}$	10,876	3354.556	89	27,785
$Club\_size_{it}$	1,688	1529.404	30	5,520
$Total\_helps_{it-1}$	146	244.347	0	2745

ond, if the answers supplied by the user are accepted as the effective solution to the corresponding questions, they may perceive a higher value of their efforts as their contribution receives recognition from the community, leading to a transition to a higher motivation state. We measure the effects of such peer recognition by the number of effective solutions provided by the user in the past, denoted by $Help\_effective_{it-1}$. Third, self-image may play a role in state transitions. In addition to inquiry-specific recognition determined by questioners, the platform organizer would publicly reward the user with an outstanding contribution through a bulletin board, in terms of offering effective solutions to a widely-concerned question. Such rewarding may signal and enhance the user's self-image. We capture this mechanism by the number of the bulletin nominations the user receives in the past, denoted by Big_events_{it-1}, Last, the platform would randomly share unsolved inquiries to the group chat channel of the location-based sub-groups on a weekly basis. As a member of the sub-group, the user may be motivated by such a subtle incentive that their contribution to the community is expected and necessary. Meanwhile, they may be aware of their group mates' exposure to the questions and expect others would step up to answer the questions, thereby less inclined to make contributions. To evaluate the effect of this intervention, we utilize the number of unsolved inquiries shared to the chat of the sub-group to which the user belongs, indicated by $Inquiries\_shared_{it-1}$.

Finally, the third variables consist of individual and community characteristics that may directly affect user contribution. First, geographic location plays an important role in the daily work of freight drivers. Therefore, inquiries posted on the platform may be closely related to the questioner's location. For instance, a driver may inquire about the policy of highway toll fees on holidays specific to her based city. Geographic location could potentially be more critical for time-urgent questions. Some urgent questions may require in-person help which can only be offered by the users at the same location. Therefore, whether a user can make contributions may rely heavily on whether their location is matched with the questioner's location. To account for this effect, we calculate $Matched\_locs_{it}$, indicating the number of locations matched between the questioners and the user i at time period t. Second, previous studies have shown that the length of time a user has spent on the platform could affect their participation activities (Zhou et al. 2019). We, therefore, utilized the number of days since user i registered as a proxy, denoted by $Tenure_{it}$. Third, the size of the community may affect user contribution. According to classic public goods models, the average level of contribution decreases with community size (Andreoni 1988). However, impure altruism models suggest that individual benefits may increase with a larger community due to the enhancement of joy gained by the number of recipients (Bénabou and Tirole 2006). Hence, we calculated the number of active users who participated in any activities at time t as a proxy of the community size, denoted by $Active\_users_{it}$. Fourth, in our context, the community is not unique because of the existence of sub-groups. We thereby included the number of members within the sub-group of user i, denoted as $Club\_size_{it}$. Last, a user may tend to make more contributions if they have participated more in the past. We then counted the cumulative number of past answers offered by the user to capture this effect, denoted by $Total\_helps_{it-1}$.

5.4 Results

5.4.1 Estimation and Model Selection

We start our estimation process with a latent class model (LCA) to estimate the initial distribution of users' motivation states. The number of hidden states in the HMM framework is an unknown hyper-parameter, which needs to be tuned over to find the value that best fits the data. We implemented a maximum likelihood method to estimate the model and applied a Levenberg-Marquardt algorithm (LM) to maximize the log-likelihood function (Levenberg 1944). Mixing a Gauss-Newton method and a gradient descent method, the LM algorithm outperforms other optimizers when the optimal parameter values are far from the initial values, which is suitable for the estimation of our model. Following previous literature (Chen et al. 2017), we adopted Bayesian information criterion and Akaike information criterion as two metrics to assist model selection respecting different hyper-parameter values. Table 5.2 presents the metrics associated with different numbers of states. According to the results, the optimal number of hidden states in our context is three. The three states are interpreted as low, medium, and high levels of the user motivation states on the focal community-based Q&A platform, denoted by L, M, and H, respectively. The estimated initial distribution of the three states derived by the LCA model is (0.212, 0.549, 0.239).

Table 5.2: Model Selection: Number of Hidden States

Number of States	**Log-likelihood**	**AIC**	**BIC**
1	-86713.14	173472.28	173585.16
2	-85418.27	170922.54	171133,57
3	**-82,187.14**	**164504.28**	**164823.28**
4	-83166.52	166511.04	166947.83

We then present the estimation results of our three-state HMM model in Table 5.3. The estimates of the parameters affecting state-dependent outcome are two-dimensional, with the first dimension representing responses to urgent questions and the second representing responses to non-urgent questions. To avoid potential label switching problem, we imposed a constraint on the constant terms incorporated in both dimensions of outcome responses such that $\beta_{0,Lk} < \beta_{0,Mk} < \beta_{0,Hk}, k = 0, 1$. Such a constraint ensures that a highly motivated user tends to respond more to both types of questions than a user residing in a lower motivation state without other influences.

The estimated thresholds appearing in the state-transition probabilities indicate the minimum *effort* an individual needs to exert in order to switch to a different state, where a negative value implies consumption of utility. In addition, the estimates of the joint distribution of the two sets of individual-level random effects are presented at the end of the table. As noted in Section 5.2.2, the jointly distributed random effects not only capture the unobserved individual-level heterogeneity but also account for potential correlations between two dimensions of the state-dependent outcome. We selected two as the number of supports for each random effect variable. After re-scaling the two variables with two normalizing parameters $C_{\eta_{i0}}$ and $C_{\eta_{i1}}$, we set the boundary for each of the variables to be between 0 and 1.

Table 5.3: Estimates of HMM Parameters[1]

Paramter	**State 1 (L)**		**State 2 (M)**		**State 3 (H)**	
Variables Affecting State-Dependent Outcome						
	Urgent	**Non-Urgent**	**Urgent**	**Non-Urgent**	**Urgent**	**Non-Urgent**
Matched_locs	0.506***	0.016	0.240***	0.241***	0.550***	0.263***
	(0.090)	(0.097)	(0.042)	(0.037)	(0.068)	(0.053)
Tenure	−0.701***	−0.583***	−0.559***	−0.866***	−0.781***	−0.877***
	(0.072)	(0.103)	(0.052)	(0.035)	(0.060)	(0.060)
Active_users	3.082***	3.586***	2.462***	2.478***	1.517***	2.336***
	(0.199)	(0.154)	(0.120)	(0.123)	(0.150)	(0.155)
Club_size	−0.074***	−0.125**	−0.080**	−0.387***	−0.020***	−0.257***
	(0.019)	(0.060)	(0.035)	(0.028)	(0.002)	(0.049)
Total_helps	0.832***	1.249***	0.607***	0.688***	0.534***	0.737***
	(0.038)	(0.072)	(0.028)	(0.033)	(0.035)	(0.031)
θ Dispersion rate	−0.652***	−0.583***	−1.722***	−2.005***	−0.705***	−0.790***
	(0.078)	(0.085)	(0.074)	(0.057)	(0.047)	(0.043)
Constant	−13.318***	−14.847***	−10.097***	−6.694***	−4.452***	−5.493***
	(0.909)	(0.643)	(0.514)	(0.540)	(0.664)	(0.688)
Variables Affecting State Transition						
Helps_received	0.193**		-0.400		0.002	
	(0.084)		(0.275)		(0.064)	
Helps_effective	0.124		0.585***		-0.178	
	(0.160)		(0.146)		(0.191)	
Big_events	-0.124		0.254*		0.089*	
	(0.180)		(0.136)		(0.044)	
Inquiries_shared	-0.427***		0.117		0.227	
	(0.157)		(0.130)		(0.189)	
Thresholds						
State 1			2.752***(0.158)		4.943***(0.239)	
State 2	-2.027***(0.147)				4.460***(0.215)	
State 3	-4.588***(0.413)		-1.718***(0.167)			
Individual-level Unobserved Heterogeneity						
Normalizing Constants: $C_{\eta_{i0}} = 1.306, C_{\eta_{i1}} = -0.988$						
	$\eta_{i1} = 0$				$\eta_{i1} = 1$	
$\eta_{i0} = 0$	0.289				0.353	
$\eta_{i0} = 1$	0.147				0.211	

[1] *Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*
[1] *All explanatory variables are log-transformed to address the skewed distribution.*

5.4.2 Motivation State Transitions

The estimates of the parameters corresponding to the variables affecting transitions of users' motivation states are reported in the second panel of Table 5.3. First, we found that when the user is in a low motivation state, the more answers they receive to their past questions, the more inclined they are to transmit to a higher motivation state ($\beta = 0.193$, $p-value < 0.05$). However, such an effect becomes insignificant when the user resides in a medium or high level of motivation stage. The results indicate that while reciprocity can take a positive effect on the lower motivation state, it becomes less powerful when the user is already highly motivated to make contributions.

Second, the results show that a higher number of acceptances of the replies provided by the focal user as effective solutions only induce a significantly higher probability to stay in or switch to a higher state when the user is moderately motivated ($\beta = 0.585$, $p-value < 0.01$). When users are already in a highly motivated state, the value they can gain from the recognition of peers in the community declines.

Third, we discovered that the public recognition from the community organizer of the outstanding contribution to widely concerned inquires serves as a positive driver of the user's motivation transition when they are in a medium or high level of motivation state ($\beta = 0.254$, $p-value < 0.1$; $\beta = 0.089$, $p-value < 0.1$). Combining with the aforementioned results, we found that for users in a low motivation state to contribute, reciprocity is the most effective incentive to move up to a higher state; for users who are moderately motivated, peer recognition and the self-image enhanced by public recognition through bulletin become more attractive, probably because the user starts to concentrate on their identity uniqueness in the community as the user is already motivated to make certain contributions; finally, for highly-motivated users, only the public nomination awarded by the community organizer works as an effective incentive, which they may perceive as a higher rank of recognition from the community as well as improvement of their self-image. Our results provide empirical evidence on the heterogeneity in effects of popular motivating mechanisms across users in different motivation states, offering practical implications to Q&A platforms.

Last but not the least, we found that surprisingly, a higher number of unsolved problems shared to the sub-group chat channel would discourage the user in a low motivation state to move to a higher state, and exhibit no significant impact on users who are already in higher states ($\beta = -0.427$, $p-value < 0.01$). A possible explanation might be supported by the social-loafing theory. When the questions are shared with the sub-group, the user is aware that their group mates also acknowledge the existence of the unsolved questions on the platform. Thus, the user may value their own duty to solve the inquiry and the necessity of their contribution less compared to the situation where they perceive themselves as bearing full responsibility to offer solutions. Our findings of such an unintended effect raise caution for Q&A platforms respecting subtle interventions within minor groups.

5.4.3 Two-Dimensional State-Dependent Outcomes

The estimates of parameters reflecting the direct effects of the variables on state-dependent outcomes are reported in the first panel of the table. In this study, we construct the outcome variable as a two-dimensional vector, comprising a user's responding behaviors to urgent and non-urgent inquiries. As shown by the results, generally speaking, the effects of individual and community characteristics on the two dimensions of users' responding activities have consistent directions. First, for freight drivers, geographic locations play an important role in their daily work. We found that a larger number of questioners' locations with the focal user's location would significantly increase users' responding behaviors. In particular, matched locations exert a higher influence on users' responses to urgent questions than non-urgent questions. Our finding is consistent with our prior expectation, as the urgent questions posted by the drivers are often related more closely to the physical location of the questioner where in-person help may sometimes be expected. Thus, the number of urgent questions a user would respond to relies heavily on their geographic scope in the community.

Second, our results show that the longer the user have stayed on the platform, the fewer contributions they would tend to make. Such a result is consistent with previous literature as well as the declining user participation ratio which has been reported by many large online communities. Specifically, we found that the effective size of users' registration tenure is larger for responses to urgent questions than to non-urgent questions when the user is in a low motivation state. However, when the user moves to higher states, a longer registration tenure would reduce users' responding behaviors to non-urgent questions more.

Third, a larger number of activity users in the whole community exhibits a significant positive effect on both dimensions of users' responding behaviors, especially to non-urgent questions. In contrast, surprisingly, we found that such an effect is reversed if we switch attention to the sub-groups the user belongs to. For the whole community, massive size of recipients may enhance the joy an individual gains from making contributions. However, for the sub-groups that individuals join within the large community, a larger size may incur a social loafing problem, such that the individual may perceive their own effort as less necessary and less urged to offer solutions. In addition, we observe a larger suppressive effect of the sub-group size on users' responses to non-urgent inquiries than to urgent inquiries. A possible explanation is that when facing urgent questions, the user may feel more responsible to offer help and value their contribution more.

Additionally, we found that users tend to contribute more if they have provided more responses in the past. Such an effect is generally higher when users face non-urgent questions. Our findings empirically show the heterogeneous effects of various individual and community characteristics across users in different motivation states as well as different time-urgency levels of the corresponding questions. Specifically, the opposite impacts of the sizes of the whole community and embedded sub-groups caution the platform to reevaluate the effectiveness of sub-groups.

5.5 Conclusion

Online communities played an essential role in providing a convenient channel where people can connect and collaborate despite the geographic difference. Specifically, the community-based Q&A platform has emerged to be a prominent knowledge-sharing type of online community. Although previous literature has investigated individuals' online activities in Q&A platforms (Chen et al. 2017), few studies discriminate individuals' responses to different types of questions. While questions posted on Q&A websites are initiated by mutual interest, they may still share different attributes. Platforms oriented in individuals with specific occupations such as freight drivers, for example, may be filled with questions of different time-urgency levels. In this paper, we aim to investigate users' responding behaviors to questions with different urgency levels and examine potential motivating mechanisms affecting their underlying motivation states as well as contributions.

To tackle this question, we implemented a multi-dimensional Hidden Markov Model. The double-layer structure of the HMM model enables us to capture the dynamics of the hidden motivation states of users through their actual observable online activities induced by the motivation states. Moreover, we construct the observed responding behavior of users as a multi-dimensional vector to account for users' responses to questions with different urgency levels. To calibrate our model, we collected data from a leading online freight-driver-oriented Q&A platform in China including information on the questions posted on the forum, corresponding replies, and characteristics of associated users.

Our analysis provides several managerial implications and theoretical contributions. First, to the best of our knowledge, this paper is among the first to investigate different dimensions of individual behaviors in online Q&A communities, with a special focus on different urgency levels of questions. Our findings provide empirical evidence on the heterogeneous effects various individual and community characteristics may incur on users' responding behaviors to urgent and non-urgent questions. Second, we add to the literature on the potential social effects of community size on individual contribution through exploring how the size of the whole community and the embedded sub-groups affect users' contributions on Q&A sites, respectively. We found that while a larger whole community can encourage the user to make more contributions, joining a sub-group with more members may reduce the perceived value of their own contribution, leading to a decrease in the responding behaviors. Last, the HMM framework allows us to explore the dynamics of the underlying motivation states of users as well as the effects of motivating mechanisms adopted by the platform. Surprisingly, we found that with more unsolved problems shared to the chat channel of the sub-group to which the user belongs, the user in a low motivation state is disinclined to move to a higher state. Our findings caution the online Q&A platform with unintended effects of the formation of sub-groups within the whole community and suggest a more subtle intervention rather than randomly sharing unsolved inquiries with sub-group members.

Our research is not without limitations. First, for ease of estimation, we fix the number of supports of individual random effects, which can serve as a hyper-parameter and be optimized in the future. Second, we aggregated the data on a weekly base due to the computational capacity limit. Future study can examine the daily activities of individuals. Finally, we didn't differentiate the effects of motivating mechanisms on users' motivation state transitions across different types of questions, which can be extended in the future.

Chapter 6

CONCLUDING REMARKS

With the rapid development of technology, online platforms have designed and employed a variety of IT artifacts to improve users' online experience and platforms' business performance. The types of such business innovations vary towards the service offered by different online platforms, which motivates this dissertation to provide a holistic view of the economic value embedded in the IT artifacts. Specifically, I inspect three related contexts: the individual decision-making process on online reading platforms, the effectiveness of a redirection-based misinformation countermeasure implemented by social media, and the multi-dimensional individuals' voluntary contribution to online communities.

In Chapter 3, I aim to examine the unique e-book selling strategies employed by online reading platforms, specifically focusing on the novel pay-by-content business model and the in-chapter online comment system. As a type of experience good, the quality of e-books can hardly be evaluated accurately prior to purchase. Thus, whether and how the aforementioned strategies facilitate the alleviation of consumers' uncertainty towards the e-book's true quality calls for inspection. To this end, I utilize a structural model grounded in consumer-level data from a popular online reading platform to examine consumer learning and decision-making processes. Using a Bayesian learning framework, I am able to evaluate consumers' abilities to ascertain the quality of a book through both their direct reading experiences and others' indirect reading experiences varied by genre. For example, books within the gender-neutral fiction genre typically provide a more stable reading experience, resulting in a faster learning curve and a more reliable perception of book quality. This finding prompts the suggestion for authors of other genres to ensure consistency in their chapters to deliver a similar stable experience. In addition, I also dive deep into the textual patterns of in-chapter comments and their signaling effects on the book quality. The analysis indicates that the nature of the comment - whether positive, neutral, or negative - and the subject of the comment - like plot discussion or requests for plot changes - significantly swayed consumers' perception of book quality. Encouraging inferences, evaluations of the character's behavior, and requests for new chapters would increase consumers' perceived book quality. On the contrary, comments filled with happy emotional words or depicting hypothetical desired plots tend to decrease consumers' perception of book quality. Finally, I find that informative chapter titles are likely to increase a consumer's interest in purchasing consecutive chapters, suggesting a potential strategy for authors to better engage readers and boost sales. Based on these findings, the study proposes that platforms could further optimize these trends by implementing specific motivation mechanisms, such as recognizing high-quality comments or providing monetary incentives like vouchers, to encourage more desirable commenting behavior and informative chapter naming from authors. Moreover, as shown by the policy simulation studies, platforms may consider using the aforementioned mechanisms to reward especially consistent contributions of the *favored types* of in-consumption comments throughout chapters, so as to encourage future consumers to read continuously.

In Chapter 4, I seek to investigate the effectiveness of a potential weapon taken by social media platforms to combat the rapid spread of public health-related misinformation. Specifically, I focus on one such misinformation policy initiated by Twitter in May 2019, inspecting its impact on the spread of true information while comparing it with that of falsehoods. Through a Differen-in-Difference analysis, I find that while the policy effectively inhibits the spread of misinformation, it can also unintentionally suppress the spread of true information. After the introduction of Twitter's intervention, all public health-related tweets are found to be less widely disseminated, regardless of their truthfulness. Although false information is more strongly suppressed, the spread of true information also suffers. A further study suggests that this could be due to the difficulty users face in discerning the truthfulness of public health information. Moreover, I find that tweets from verified authoritative sources in public health fields experience an increase in spread following the policy's introduction, suggesting that users rely more heavily on the credibility of the account when they find it difficult to judge the truthfulness of the content. Finally, I explore the characteristics of tweets that can potentially affect people's belief in them through a correlational analysis. This study provides crucial insights into the unintended side effects of misinformation policies and calls for platforms to implement more precise strategies that can differentiate between true and false information while encouraging the spread of accurate public health information.

In Chapter 5, I examine users' participation on community-based Q&A platforms, particularly focusing on their responses to questions with different time-urgency levels. Utilizing a multi-dimensional Hidden Markov Model, I investigate the dynamics of latent motivation states of users and how these states drive observable online activities. The study applies data from a leading online freight driver-oriented Q&A platform in China, capturing the dynamics of posted questions, corresponding replies, and user characteristics. I summarize the major findings as follows. Firstly, the study offers a novel investigation into multiple dimensions of individual behaviors in online Q&A communities, focusing on the urgency level of questions. The results reveal the heterogeneous effects individual and community characteristics can have on users' responding behaviors to urgent and non-urgent questions. Secondly, the research adds to the understanding of the social effects of community size on individual contributions. I find that while larger communities may stimulate more user contributions, participation in larger sub-groups could decrease perceived individual value and thus reduce users' responding behaviors. Lastly, I discover that sharing more unsolved problems within a sub-group's chat channel could discourage users in a low motivation state from advancing to a higher motivation state. These findings highlight the unintended effects of sub-group formations within broader communities and suggest more nuanced interventions rather than randomly sharing unsolved inquiries with sub-group members.

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Appendix A

ONLINE APPENDIX OF LEARNING WHEN READING: EVIDENCE FROM AN ONLINE MOBILE READING PLATFORM

A.1 Reduced-form Evidence on In-consumption Social Listening Effects

We construct a reduced-form model to examine evidence on the impacts of in-consumption comments on consumers' purchase decisions. Specifically, we model consumers' chapter selection as the number of chapters that they decide to skip at the end of each chapter they consume, that follows a negative binomial distribution. The proposed model is as follows:

$$\begin{aligned}
Prob(N_{im[j]t} = n) = & \frac{\Gamma(\theta+n)\theta^{\theta}\lambda^{n}_{im[j]t}}{\Gamma(n+1)\Gamma(\theta)(\lambda_{im[j]t}+\theta)^{\theta+n}} \\
\lambda_{im[j]t} = & exp(U_{im[j]t}) \\
U_{im[j]t} = & \beta_0 + \beta_1 \cdot Price_{im[j]t} + \beta_2 \cdot TotalSpend_{im[j]t} + \beta_3 \cdot Informativeness_{im[j]t} + \beta_4 \cdot Position_{im[j]t} \\
& + \sum_{k=1}^{5} \beta_{5k} \cdot BulCluster_{im[j]t,k} + \varepsilon_{im[j]t}
\end{aligned} \tag{A.1}$$

where $N_{im[j]t}$ denotes the number of skipped chapters by consumer i at the end of chapter t of book m.

The results are reported in Table A.1.1. Our findings indicate that the volume of in-consumption comments across five topics has varying impacts on consumers' purchase decisions. The directions of the effects of these comment topics align with our main model estimation results as well as our expectations based on the conceptual framework, as detailed in Section3.4. Specifically, consumers facing more comments making inferences based on the narrative, judging the character's behaviors, or pleading for the release of new chapters tend to skip fewer chapters. On the contrary, an increased volume of comments comprising merely happy emotional words or those depicting a desired hypothetical future scene could increase consumers' intention to skip more chapters.

However, this model alone fails to capture consumers' hidden, dynamic perceived quality of the book, which is derived from their own experience as well as in-consumption social listening. Therefore, we develop a Bayesian learning model to unveil the underlying mechanisms of consumers' decision-making process.

Table A.1.1: Baseline Results[1]

Variables	Estimate	Std. error
Intercept	$-1.58***$	0.14
Topic-1 Comment Volume[2]	$9.77*$	4.78
Topic-2 Comment Volume	$-9.97**$	3.56
Topic-3 Comment Volume	$-9.72*$	4.87
Topic-4 Comment Volume	$10.57*$	4.21
Topic-5 Comment Volume	$-9.66*$	4.14
Price	0.37	0.29
TotalSpend	$-0.87*$	0.41
Informativeness	$-1.36***$	0.14
Position	$4.52***$	1.70

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*
[2] *The comment volume is log-transformed.*

A.2 Validating the Classification of In-consumption Comments Topics

To determine the optimal number of topic clusters, we utilize the elbow method, which calculates the within-cluster sum of square (WCSS), which is the sum of the squared distance between each point and the centroid in a cluster, and plotted the value across different numbers of clusters. As shown in Figure A.2.1, WCSS would rapidly change at a point, thus creating an elbow shape. From this point, the graph starts to move almost parallel to the X-axis. This turning point denotes the optimal number of topic clusters existing among in-consumption comments.

We justify our classification analysis of the comment topics as follows. First, we choose a k-means model over a Latent Dirichlet Allocation model because the in-consumption comments are all very short (i.e., less than 10 Chinese words). LDA model is shown to have a relatively poor performance for short text (Hong and Davison 2010). Second, we calculate the average silhouette width, which is another commonly used metric to select the optimal parameter of a k-means model

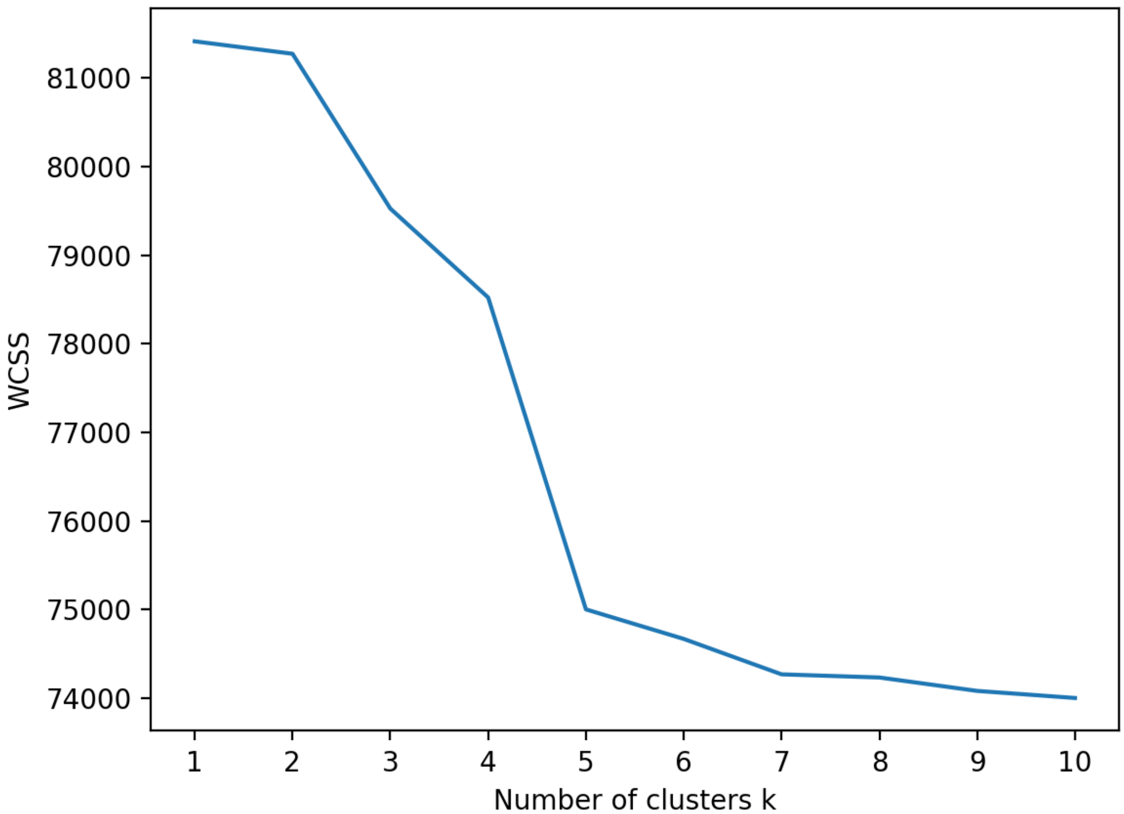

Figure A.2.1: Elbow Figrue

(Rousseeuw 1987), to ensure the robustness of our findings. Consistently, the results reaffirmed the presence of five topics, as initially discovered. Additionally, we explore the potential of classifying the comments into fewer or more categories. However, these alternative classifications resulted in a decrease in interpretability, suggesting that they did not capture the nuances of the comments as effectively as our original five-topic classification. Based on these comprehensive analyses, we concluded that our initial classification of in-consumption comment topics remains the most accurate and interpretable.

A.3 Mundlak's Approach

Mundlak's approach starts by including time-invariant fixed effects in a panel data model to address potential correlated omitted variables concerns. Instead of introducing common fixed effects that are free from assumptions on their dependence on observed explanatory variables, Mundlak places substantive restrictions on the distribution of the fixed effects given the explanatory variables. Specifically, considering a panel data model with time-invariant fixed effects, c_i, and the associative explanatory variables, $\mathbf{x_{it}}$, the CRE framework makes the following assumption:

$$c_i|\mathbf{x_i} \sim Normal(\psi + \bar{\mathbf{x}}_\mathbf{i}\xi, \sigma^2) \tag{A.2}$$

where $\bar{\mathbf{x}}_\mathbf{i}$ is the average of $\mathbf{x_{it}}$ across all time periods, and σ^2 is the conditional variance of c_i, which is assumed to be independent of $\mathbf{x_i}$. Hence, the original model can be rewritten by replacing the fixed effects with the averages of potential endogenous explanatory variables over the time periods.

A.4 Constructing the Likelihood Function

Because we are unable to observe the values of the experiential signal generated from consumer learning processes, the probability of the observed reading history for consumer i on book $m[j]$, denoted by $H_{im[j]}$, is written as follows:

$$Prob(H_{im[j]}) = \int_{\delta_{im[j]t}} \prod_{t=1}^{T_{m[j]}} P(N_{im[j]t}) dF(\delta_{im[j]t}) \tag{A.3}$$

where $T_{m[j]}$ indicates the total number of chapters in book $m[j]$. We simulate this integral using draws for $\delta_{im[j]t}$ from its distribution specified in Equation 3.1, applying the widely-used Monte Carlo simulation method with a simulation size of 100 (Sawilowsky 2003).

We then define the residuals in the content-quality relationship (3.4) as $\omega_{im[j]t,k} = ln(1 + Bul_{im[j]t,k}) - Bul_{0,k} - \phi_k * \alpha_j - \eta_{j,k}$. Let $f(\omega)$ denotes the intensities of ω, the simulated likelihood for consumer i is:

$$L_i = \prod_{m[j]} \prod_{t} \prod_{k=1}^{5} (1 + Bul_{im[j]t,k})^{-1} f(\omega_{im[j]t,k}) Prob(H_{im[j]}) \tag{A.4}$$

Notably, here the term $(1 + Bul_{im[j]t,k})^{-1}$ is generated by the Jacobian.

The likelihood for the complete reading history for all consumers on all books, denoted by H, is thus specified as below:

$$L(H) = \prod_{i=1} L_i \tag{A.5}$$

A.5 Procedures of Policy 2: Decreasing Comment Variability

We follow the following procedure to decrease the variability of the in-consumption comment volume while keeping the mean volume unchanged: (1) we find the mean comment volume for each book-genre-comment-topic pair; (2) we scale down the deviation of the volume realizations from that mean value to achieve the desired decrease in variance; (3) we determine how such a transformation affects mean and variance of log comment volume; (4) we modify the log comment volume equation (3.2) accordingly to keep the mean comment volume fixed; (5) we simulate consumers' behavior given the new comment volume data and the new comment volume process.

A.6 Tables

A.7 Figures

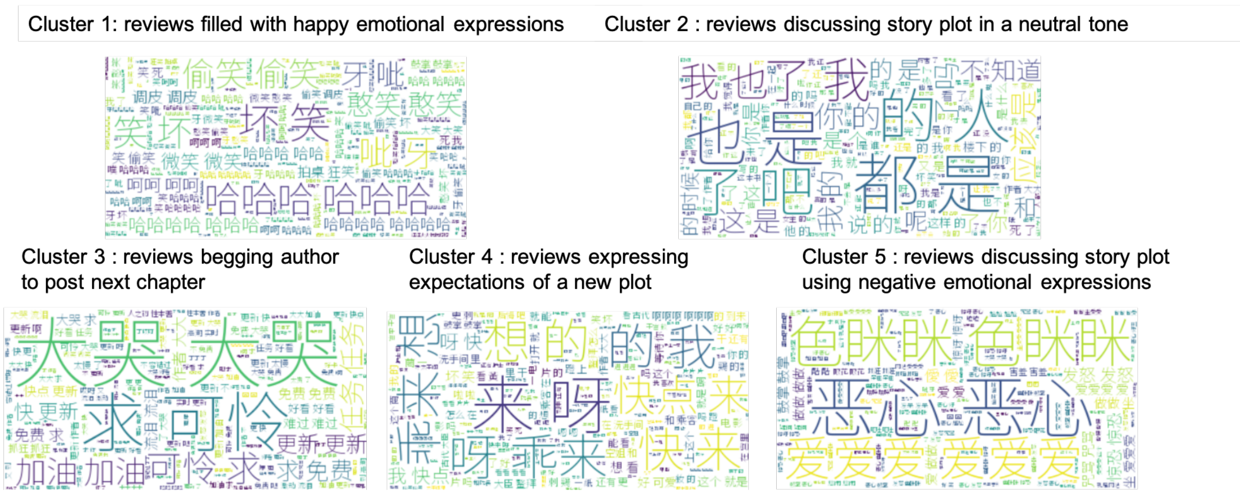

Figure A.7.1: In-consumption comment topics in Chinese.

Table A.6.1: Parameter Estimates: Full Table[1]

Paramter	Estimate	Std. error
Consecutive Reading		
Price	0.21	0.18
TotalSpend	-1.22^{***}	0.16
Perceived Quality	4.68^{***}	0.42
Returning to Chapter List		
Price	0.33^{***}	0.11
TotalSpend	-2.42^{***}	0.30
Perceived Quality	3.73^{***}	0.34
Skipping Chapter		
Informativeness	-1.78^{***}	0.04
Position	5.78^{***}	0.18
Perceived Quality	-2.02^{***}	0.00
TotalSpend	-1.36^{***}	0.11
θ	0.01^{***}	0.00
Experiential Signaling Parameters		
α_{01}(Mean prior quality belief of Book Genre 1)	-110.18^{***}	14.76
α_{02}(Mean prior quality belief of Book Genre 2)	-113.10^{***}	16.13
α_{03}(Mean prior quality belief of Book Genre 3)	-68.96^{***}	14.20
α_{04}(Mean prior quality belief of Book Genre 4)	-122.70^{***}	15.40
τ_1^2(Experiential Signal Variance of Book Genre 1)	10.57^{***}	2.22
τ_2^2(Experiential Signal Variance of Book Genre 2)	18.27^{***}	7.63
τ_3^2(Experiential Signal Variance of Book Genre 3)	4.54^{***}	1.02
τ_4^2(Experiential Signal Variance of Book Genre 4)	20.71^{***}	7.72
Social-Listening Signaling Parameters		
$Bul_{0,1}$(Intercept of Topic-1 Comment)	0.22^{***}	0.01
$Bul_{0,2}$(Intercept of Topic-2 Comment)	0.22^{***}	0.01
$Bul_{0,3}$(Intercept of Topic-3 Comment)	1.07^{***}	0.01
$Bul_{0,4}$(Intercept of Topic-4 Comment)	0.18^{***}	0.01
$Bul_{0,5}$(Intercept of Topic-5 Comment)	0.65^{***}	0.01
ϕ_1(Slope of Topic-1 Comment Signaling Equation)	-0.32^{***}	0.05
ϕ_2(Slope of Topic-2 Comment Signaling Equation)	4.85^{***}	0.24
ϕ_3(Slope of Topic-3 Comment Signaling Equation)	1.41^{***}	0.37
ϕ_4(Slope of Topic-4 Comment Signaling Equation)	-1.93^{***}	0.65
ϕ_5(Slope of Topic-5 Comment Signaling Equation)	0.50^{***}	0.75
$\sigma^2_{\eta,1}$(Variance of Genre-specific Constants)	3.34^{***}	0.67
$\sigma^2_{\eta,2}$(Variance of Genre-specific Constants)	1.26^{***}	0.11
$\sigma^2_{\eta,3}$(Variance of Genre-specific Constants)	4.62^{***}	0.58
$\sigma^2_{\eta,4}$(Variance of Genre-specific Constants)	7.90^{***}	0.18
$\sigma^2_{\eta,5}$(Variance of Genre-specific Constants)	1.63^{***}	0.44
$\sigma^2_{\omega,1}$(Topic-1 Comment Volume Variability)	0.96^{***}	0.02
$\sigma^2_{\omega,2}$(Topic-1 Comment Volume Variability)	0.85^{***}	0.01
$\sigma^2_{\omega,3}$(Topic-1 Comment Volume Variability)	1.32^{***}	0.01
$\sigma^2_{\omega,4}$(Topic-1 Comment Volume Variability)	0.74^{***}	0.02
$\sigma^2_{\omega,5}$(Topic-1 Comment Volume Variability)	1.19^{***}	0.04
$\eta_{1,1}$	-0.18^{***}	0.01
$\eta_{1,2}$	-0.15^{***}	0.01
$\eta_{1,3}$	-0.22^{***}	0.01
$\eta_{1,4}$	-0.11^{***}	0.01
$\eta_{1,5}$	-0.19^{***}	0.01
$\eta_{2,1}$	-0.21^{***}	0.04
$\eta_{2,2}$	-0.14^{***}	0.02
$\eta_{2,3}$	-0.25^{***}	0.01
$\eta_{2,4}$	-0.16^{***}	0.02
$\eta_{2,5}$	-0.29^{***}	0.01
$\eta_{3,1}$	-0.18^{***}	0.02
$\eta_{3,2}$	-0.10^{***}	0.02
$\eta_{3,3}$	0.12^{***}	0.01
$\eta_{3,4}$	-0.15^{***}	0.02
$\eta_{3,5}$	-0.15^{***}	0.03
$\eta_{4,1}$	0.57^{***}	0.01
$\eta_{4,2}$	0.40^{***}	0.01
$\eta_{4,3}$	0.36^{***}	0.01
$\eta_{4,4}$	0.42^{***}	0.02
$\eta_{4,5}$	0.62^{***}	0.01

[1] *Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

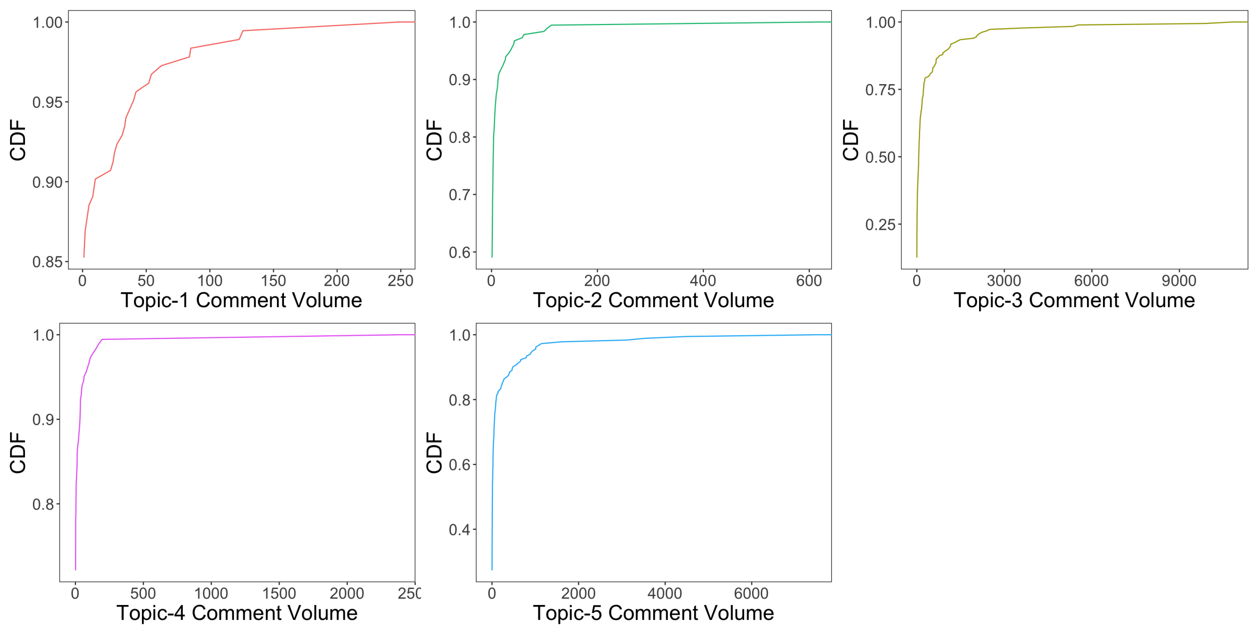

Figure A.7.2: CDF of the in-consumption comment volume across five topics within male sensational fiction

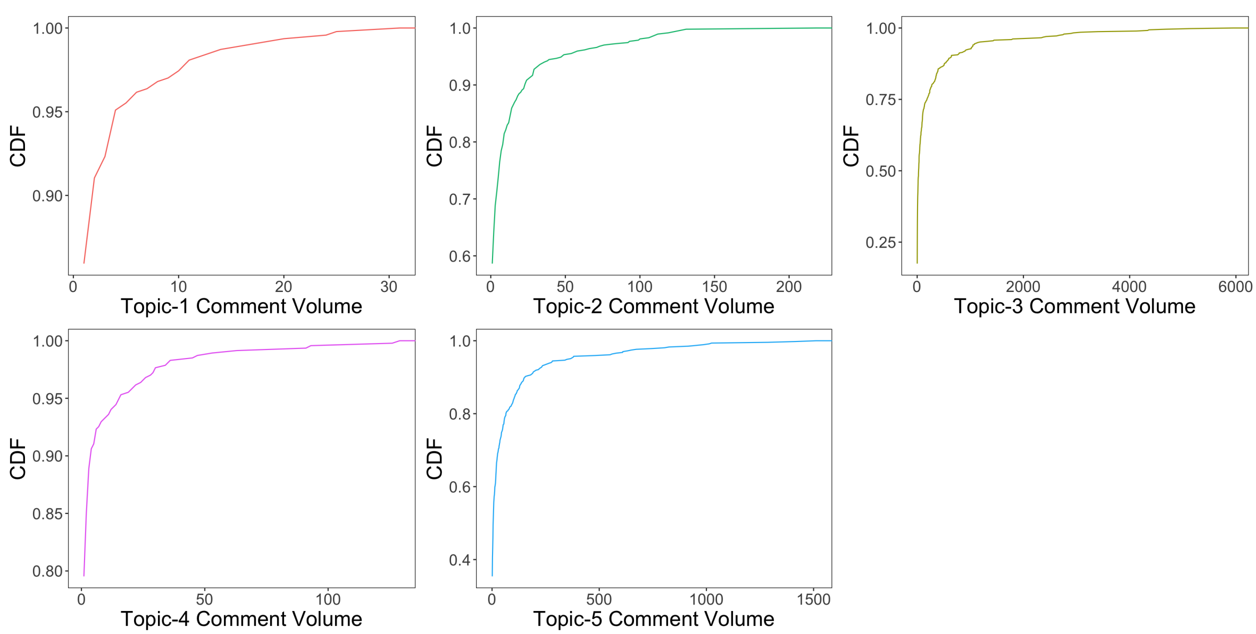

Figure A.7.3: CDF of the in-consumption comment volume across five topics within female sensational fiction

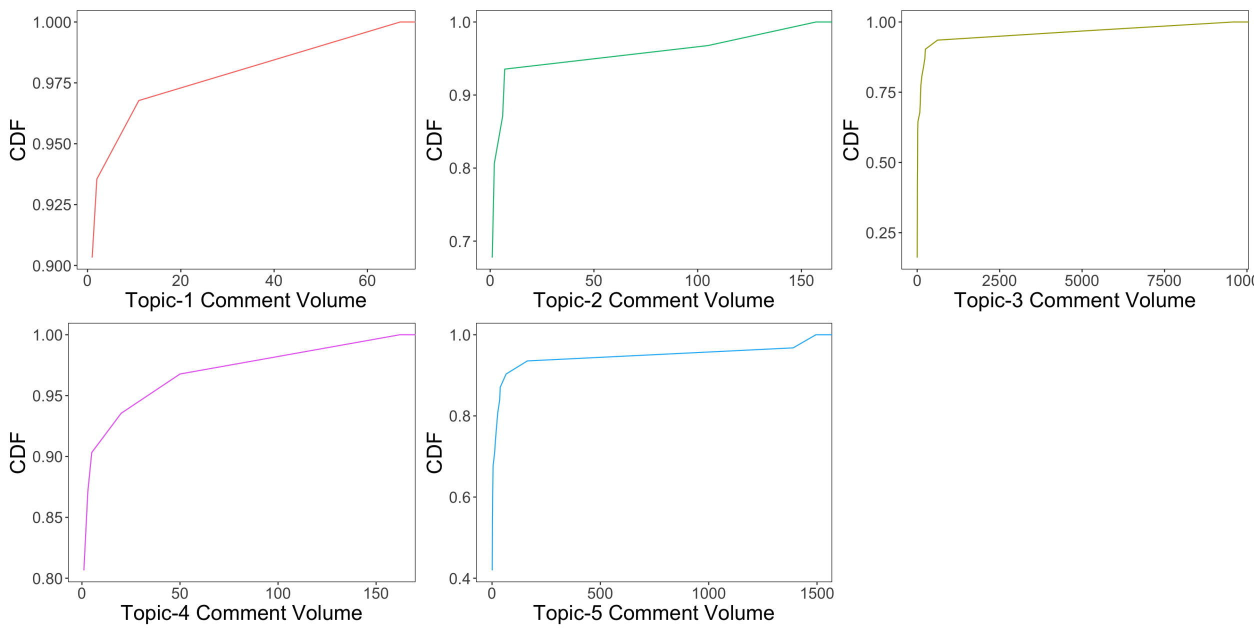

Figure A.7.4: CDF of the in-consumption comment volume across five topics within gender-neutral fiction

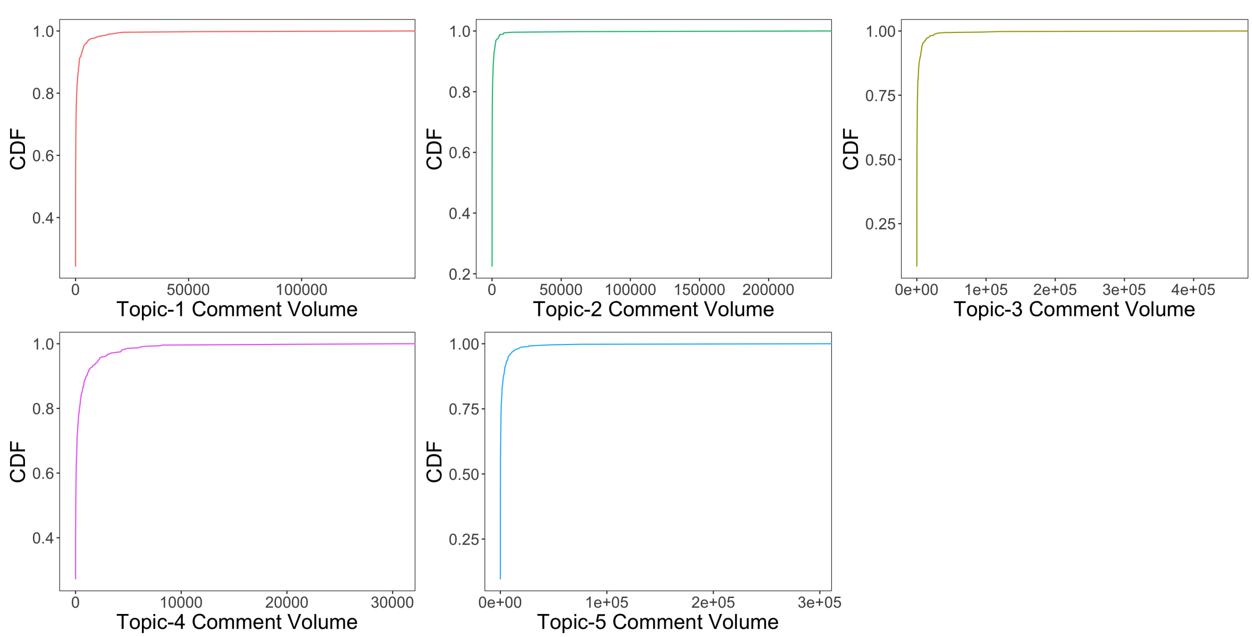

Figure A.7.5: CDF of the in-consumption comment volume across five topics within teen fiction