Mutual Disclosures and Content Intimacy in User Engagement: Evidence from an Online Chat Group

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Abstract. This paper investigates the role of self-disclosure in online chat groups (OCGs), which serve as a communication channel situated between public platforms and private live chats. Our investigation delves into the effects of mutual disclosures, originating from other members and focal users, on user engagement in terms of promptness, positivity, and effort. We also explore the disclosure content and the interplay between mutual disclosures regarding consistency in content intimacy. Using data from a retailer who utilizes OCGs for customer services, our findings reveal that mutual disclosures are positively associated with user engagement through the mechanism of liking and uncover multifaceted influences from content intimacy consistency between mutual disclosures. The results are further verified by a controlled experiment and various robustness tests. Moreover, our study differentiates and discusses the roles of group hosts and peer users in facilitating OCG engagement. This research broadens our understanding of how self-related information exchange in online group conversations promotes meaningful engagement. Our fine-grained analysis of disclosure interactions provides clear guidance for firms to strategically manage customer relationships through OCGs and sheds new light on conversational commerce.

Keywords: online chat groups, self-disclosure, mutual disclosures, content intimacy consistency, user engagement

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1. INTRODUCTION

Over the last two decades, the rapid development of information technologies has allowed online users to interact with each other through social networks. By harnessing this power, firms have developed various strategies to engage customers. One example is to create brand communities on public platforms (e.g., Facebook business pages) to boost discussions and collect user opinions (Yang et al. 2019). Meanwhile, empowered by instant messaging technologies, some firms adopt live chat tools to provide customer services in a one-to-one mode (Tan et al. 2019), as a replacement for traditional ways such as through phone calls or in-person visits. One emerging communication channel situated between public platforms and private live chats is Online Chat Group (OCG). OCGs are a type of *semi-private* community connecting a group of users who can send instant messages and exchange information among group members.

A plethora of social networking tools, including WhatsApp, WeChat, and Facebook Messenger, support OCGs, and there are also specialized group chat apps such as Band and Discord. Furthermore, it has become increasingly popular to incorporate chat rooms into diverse applications like Zoom and video games. OCGs can be established for various purposes. Some groups are event-driven, focusing on time-sensitive topics, and may disband rapidly (e.g., discussing a short trip, scheduling a meeting, or planning a meal together) (Qiu et al. 2016). In contrast, others are primarily centered on social interactions with the aim of fostering long-term relationships through regular engagements. These encompass work groups, fan clubs, gaming communities, customer forums, and more.

Companies can exploit OCGs to simultaneously offer services to groups of customers, foster customer interactions, and manage customer relationships in a more responsive and devoted way. Qiu et al. (2016) analyzed the activity logs of WeChat group messages over a month and found that 40% of groups, including those aiming for long-term engagement, went dormant within just one week. Understanding how to sustain an active level of user participation in OCGs is a pressing yet unresolved issue for both OCG service providers and group hosts looking to retain users and subsequently generate business value. In this study, we narrow our focus to OCGs facilitated by companies for customer service and strive to comprehend user engagement within this context.

In comparison to user posts on public platforms, OCGs offer a more *exclusive* communication environment, as users must receive an invitation to join a group. This requirement creates a community boundary, ensuring that discussions within OCGs are not openly accessible to the public. Intrinsically, content generation in OCGs is *conversation-centric*, facilitated by instant messaging, which distinguishes it from user posts on online platforms. Unlike the one-to-one chat mode, OCGs enable *simultaneous interactions* among multiple users. Additionally, OCGs often allow for *anonymity* among users. Consequently, individuals are more inclined to share personal experiences, opinions, and emotions with fellow members in OCGs, as opposed to what is common on public platforms or in one-to-one chats. In psychological theory, sharing personal information with others is defined as self-disclosure (Cozby 1973). Inspired by the unique semi-private nature of OCGs and the prominence of self-disclosure in this environment, our study seeks to explore how disclosures from various sources are related to user engagement in online group discussions.[1]

Many existing studies have studied user engagement in terms of user-generated content (UGC) on online platforms (Ordenes et al. 2019; Yang et al. 2019). However, the effect of self-disclosure among users on content generation remains underexplored. Moreover, most prior studies rely on the volume and valence measures of user posts on public platforms to quantify engagement (e.g., Huang et al. 2017; Pu et al. 2020). Since users engage in OCGs through instant conversations, the promptness of replies becomes another vital indicator to gauge their involvement. In this study, we further account for the time-sensitive nature of conversations and examine three outcomes of user engagement in OCGs: *promptness, positivity* and *effort*.

According to the disclosure–liking framework (Collins & Miller 1994), we distinguish the effect of disclosure by disclosing sources, i.e., disclosure from others to a focal person and disclosure from the focal person to others, which together we refer to as *mutual disclosures* in OCG conversations. The two directions of disclosures are often confounded and warrant further study to disentangle their mechanisms. In this study, we evaluate the synergistic effects of mutual disclosures on focal users' subsequent engagement in OCGs. Moreover, we delve into disclosure content and explore the interplay between mutual disclosures regarding content intimacy consistency. We code disclosure content into cognitive and emotional (positive and negative) disclosures, representing different intimacy levels from intermediate to the highest (Morton 1978). Our paper aims to address the following research questions:

Q1. How do mutual disclosures among OCG users relate to focal user engagement?
Q2. How do the interactions between mutual disclosures with different content intimacy relate to focal user engagement?

The data of this study was provided by KidsWant (haiziwang.com), a leading retailer in China that sells maternal and infant supplies. Each registered customer is randomly assigned to a brand manager of the retailer in the same city. The brand managers manage their allocated customers through OCGs built on WeChat for follow-up services.[2] We

[1] The word "disclosure" throughout the paper refers to "self-disclosure".
[2] WeChat is an instant messaging social networking tool widely adopted by over 1 billion monthly active users worldwide

collect the messages in the OCGs and the groups' and brand managers' information from May 2017 to November 2018. The final sample includes 683,254 text messages from 68 groups. We match the sample concerning focal users' self-disclosure based on group and individual characteristics daily, and examine the effects of mutual disclosures on focal users' engagement promptness, positivity, and effort in the subsequent week. A controlled experiment further verifies the relationships between mutual disclosures and user engagement, and the mediation effect of liking. To draw practical insights, we further categorize the disclosures from other members into those made by peer users and those made by group hosts. This distinction allows us to investigate their differing effects on the engagement of the focal user.

Our results show that disclosures sent to and from focal users are associated with faster responses, more positive messages, and greater effort in following conversations. There are positive interactions between mutual disclosures. In addition, we find multifaceted influences from content intimacy consistency of mutual disclosures. Overall, users prefer being understood in interpersonal relationships. The mutual disclosures with consistent cognitive and emotional content can encourage quicker, more positive, and greater future engagement. Regarding the situations with inconsistent content intimacy, the relationships are not completely negative. Others' positive disclosure in conjunction with focal users' cognitive content makes them comfortable to engage further, and focal users like cognitive disclosure to help them recover from negative emotions. Interestingly, our results indicate that group hosts typically share minimal personal information, and at times, their disclosures are even detrimental to user engagement. On the other hand, peer users, who often have common experiences and concerns, are more likely to elicit empathy and foster discussions among themselves.

Our research makes contributions in several ways. First, our study investigates a prominent communication channel – OCG, which is situated between public platforms and private live chats regarding its community scope. We theorize the unique features of OCG and consequent user engagement behaviors. Particularly, our study introduces promptness based on the time dimension to characterize user engagement in chat mode. We also bring positivity and effort measures from traditional online platforms and assess the consequences in the OCG context. Collectively, these variables paint a more comprehensive picture of user behaviors in OCGs and contribute to our understanding of OCGs. Second, our study enriches the UGC literature by examining it through the lens of self-disclosure. Considering the prominence and immediacy of personal sharing in OCGs, this paper broadens our comprehension of user content generation by investigating the role of self-related information exchange. Third, drawing upon the self-disclosure theory, our research distinguishes the effects of disclosure in two dimensions. The findings reveal the synergistic effects of mutual disclosures on user engagement, and the intricate interplay between disclosures when varied levels of content intimacy are combined. Our study advances the psychological literature on self-disclosure by broadening the understanding of disclosure interactions in terms of both disclosure breadth (quantity) and disclosure depth (nature of content) within the context of OCGs. Our research findings offer concrete guidance for enhancing user engagement in OCG discussions and underscore the significance of integrating disclosure interactions. These findings have important practical implications for OCG hosts and service providers and offer valuable insights into communication design for customer services. Additionally, this research assists companies in formulating effective strategies for customer relationship management by utilizing OCGs as a tool.

2. THEORETICAL BACKGROUND

2.1. Online Chat Groups

Businesses have relied heavily on online channels to engage customers. A stream of literature has focused on understanding user behaviors on third-party review platforms (e.g., Chen et al. 2019; Lu et al. 2013) or social media business pages (e.g., Lee et al. 2018; Yang et al. 2019). A salient feature of these platforms is their public nature. That is, any users can post their opinions on the platforms, and meanwhile, read others' posts without community boundaries. Arvidsson and Caliandro (2016) create the concept of brand publics which are social formations not based on interaction but on a continuous focus of interest and mediation. Different from the case of brand communities, publicity rather than identity has become a core value. Such social media participation is by definition not community oriented because users do not have enduring social bonds around brands or consistent collective identity. On the other end of the spectrum, built on instant messaging techniques, one-to-one online live chat has been employed in many businesses to offer customer services. Agents can provide individual services to customers via an online chat interface by transmitting text messages privately. Recent research has explored the value of this service channel. For instance, Tan et al. (2019) investigate the effect of live chat on product purchases on the Alibaba platform, where buyers can communicate with sellers in real-time by using the "Trade Manager" chat tool. Benefiting from this synchronous feature, the live chat tool helps reduce information asymmetry and fosters a strong customer relationship. Goes et al. (2018) also study customer services through one-to-one live chats. However, instead of advocating a positive role, they demonstrate that live chat services

(https://en.wikipedia.org/wiki/WeChat).

might have a negative consequence on customer satisfaction. This is because agents are required to handle chat services for multiple customers simultaneously due to efficiency considerations in real businesses and switch their attention from one conversation to another. Such multitasking will lead to longer in-service delays and lower problem resolution rates and reduce customer satisfaction.

Therefore, one feasible solution is to combine individual users by forming an OCG, so that one user can send messages visible to the entire group at once. In comparison to public platforms and private (one-to-one) chat channels, the OCGs fit in between and are characterized as a *semi-private* community connecting a group of users who can exchange information with each other on a common focus. As a result, OCGs can leverage the benefits of live chat and meanwhile bring users a stronger sense of community, thus facilitating effective intragroup user interactions.

A typical OCG is created by a group host and is composed of a group of users who join upon invitation. Compared to public platforms or private chat channels, OCGs have several features. First, they provide an *exclusive* communication environment. Users join an OCG upon invitation from the group host, or in some cases from another peer user. For example, in a customer service OCG, a brand manager creates the group and invites her clients to join. There is usually a limit on the number of members in an OCG (e.g., up to 500 for WeChat groups (Qiu et al. 2016)). This restriction creates a community boundary and guarantees that the content discussed within an OCG is not accessible to the public unless someone in the group intentionally disseminates it. By contrast, users who follow a Facebook business page can freely read others' posts on the page. Therefore, OCGs enable users to discuss issues in a more private manner and thus allow them to *share more personal information* in group conversations. Second, OCGs are *conversation-centric* and consist of instant messages. This chat mode is distinguished from user posts on most online platforms, where users interact with others by creating posts and liking/commenting on others' posts (Lee et al. 2018; Yang et al. 2019). Instead, users engage in OCGs through live conversations and interact with each other by sending or replying to messages. Therefore, the promptness of their responses in group conversations is another critical indicator of user involvement in this community. Moreover, such interactive and instant conversations avoid long-time gaps between messages and do not allow users to have much time to construct and refine their content (Berger & Iyengar 2013). Consequently, users are more likely to share opinions and emotions in *real-time*. Third, overcoming the limitation of one-to-one chat, OCGs enable *simultaneous user interactions* among group members. The messages sent in the group are by default visible to the entire group, even if one message pinpoints a particular user. Users usually switch to a one-to-one chat interface if they want to chat individually. This feature ensures group-level engagement in OCGs. Fourth, while users join an OCG by invitation from someone in the group, they can intentionally hide their real-life identities by editing their alias and thus keep their identity *anonymous*. After invitation by a brand manager, users cannot figure out other customers' real identities and do not necessarily know each other offline. Previous research has shown that anonymity can reduce discomfort in conversations, allowing people to discuss more controversial topics (Chen & Berger 2013). In this sense, users can be less concerned about disclosing personal information in such OCGs.

Given the exclusive, conversational, interactive, and anonymous nature of OCGs, users are likely to be self-disclosing (i.e., exchanging personal experiences, opinions, and feelings) with each other in group conversations. Motivated by the unique community scope of OCGs and these consequential features, in this paper, we focus on the examination of self-disclosure among OCG users.

2.2. User Engagement in Online Chat Groups

OCGs differ from traditional online platforms in that they primarily utilize live chat and instant messaging to facilitate communication among users, rather than relying on webpage posts. Consequently, the ability to receive swift responses is crucial in encouraging users to actively engage in OCGs, as it fosters more efficient communication. To account for this time-sensitive nature of OCG interactions, we first employ *promptness* of responses as a metric to assess user engagement in OCGs. Moreover, featured as a semi-private community, OCGs share some similarities with public platforms and facilitate user interactions through generated content. Therefore, we refer to user engagement outcomes on public platforms in the previous UGC literature and aim to evaluate the effects on those outcomes in the context of OCGs. Yang et al. (2019) investigate two types of customer engagement on Facebook business pages: liking and commenting on a post, stating that engagement behavior can differ in the level of users' emotional expression and cognitive effort. Pu et al. (2020) examine user content generation from two perspectives: content volume and user effort. Huang et al. (2017) study the effect of social network integration on the emotional and cognitive processes of online review generation based on linguistic features. Given these insights, we further conceptualize user engagement in OCGs based on their *positivity* and *effort* in conversations to represent users' emotional and cognitive commitment, respectively. All three outcomes can indicate the level of interest users have towards OCGs. As Bateman et al. (2011) point out, people who strongly commit to a community tend to like it and participate in it.

Regarding the antecedents of user engagement, many previous studies have been developed to uncover the roles of feature designs in various platforms. For instance, Huang et al. (2019) study the design of performance feedback. Drawing on social value orientation theory, they find that the effects of feedback framing on content generation vary with user gender. Pu et al. (2020) examine user content generation motivated by a platform change of disclosing users' identities in written reviews. The results show that users are less willing to contribute content but spend greater effort on each review because disclosing identity increases social presence, and users want to achieve a better image. Recent research has emphasized the importance of information content. Yang et al. (2019) find that in addition to the effect of post valence, information content plays significant and different roles in influencing liking and commenting behaviors. Based on the speech act theory, Ordenes et al. (2019) study customer sharing of brand messages on Facebook and Twitter by evaluating the effects of linguistic characteristics in the content. Few studies have considered the effects of user interactions on focal user engagement. Chen et al. (2018) highlight the role of reciprocity in user contribution to a knowledge-sharing platform. They find that the users who have received answers to their past questions from other users will also provide more answers on the platform. Nevertheless, little research has been devoted to investigating the effect of information exchange among users, particularly from the perspective of self-disclosure, on user engagement in online group conversations. Our research fills this gap in understanding the effects of mutual disclosures between users and content intimacy in the disclosure dialogue on user engagement in OCGs.

2.3. Theory of Self-Disclosure

Self-disclosure, defined as a person communicating *any information about themselves* to another person (Cozby 1973; Wheeless 1976), has long been emphasized and investigated in the psychology literature to describe the process of interacting with others. Previous studies on social media or other online communities examine disclosure behaviors in terms of the visibility of user profiles, such as identities, interests, and political views (Cavusoglu et al. 2016; Pu et al. 2020). Some studies compare the degree of self-disclosure in different contexts. Their results show that text-based computer-mediated communication conveys higher levels of disclosure than face-to-face interactions (e.g., Gieselmann & Pietrowsky 2016; Schouten et al. 2009). Particularly, Yang et al. (2019) find that self-disclosure is reciprocated more in the private channel compared to the public channel. Drag (1969) shows through an experiment that participants in smaller groups disclose more to each other than in larger groups when the experimenter does not join the discussion and self-disclose. In light of the existing research evidence and OCG features, self-disclosure should be more salient in OCGs than on public platforms.

It has been verified that self-disclosure facilitates liking and intimate feelings (Dindia 2002) and leads to positive affect and well-being (Mehl et al. 2010). Collins and Miller (1994) propose a framework to illustrate the relationships between *disclosure and liking* for two actors (i.e., John and Mary in Fig. 1, pp. 458 in Collins & Miller 1994). Specifically, there are two possible effects generated by disclosure: (1) we like those who disclose to us (Effect 1 in the Fig. 1 of Collins & Miller 1994), and (2) we like people as a result of disclosing to them (Effect 3 in the Fig. 1 of Collins & Miller 1994). The two arrows pointing to "John likes Mary" indicate the effects of self-disclosure from opposite sources. Viewing "John" as the focal person, both disclosure *from others to the focal person* and disclosure *from the focal person to others* will affect the focal person's liking. Moreover, reciprocity of disclosure occurs when the mutual disclosures are correlated, where a person will receive more disclosure from others if they disclose to others more, and vice versa (Jourard 1959). However, the two effects of receiving others' disclosure and disclosing to others have not been sufficiently distinguished in previous UGC studies and warrant further study to understand their mechanisms separately. In this paper, we explore mutual disclosures in the two directions to elucidate their roles in online group conversations.

2.4. Measurement of Self-Disclosure

The degree of disclosure is typically evaluated by the dimensions of *breadth* and *depth* (Altman & Taylor 1973), where breadth refers to the *amount* of information exchanged, and depth refers to the *intimacy level* of the disclosure. The measurement of disclosure in the existing literature can generally be grouped into two categories. One group of studies uses survey and questionnaires. The most widely adopted instrument is Jourard's Self-Disclosure Questionnaire (JSDQ), which was initially developed by Jourard and Lasakow (1958) and has been adopted by many psychological studies (e.g., Pederson & Higbee 1968; Taylor 1968). However, as Cozby (1973) noted, JSQD may not accurately reflect the degree of actual disclosure.

Another group of studies measures self-disclosure based on textual content. Table 1 summarizes the literature using linguistic measures. Particularly, a common measure of self-disclosure is the usage of first-person words (such as I, my, we, and our) (e.g., Gieselmann & Pietrowsky 2016; Kashian et al. 2017; Melumad & Meyer 2020). People tend to use first-person pronouns in the text to highlight aspects of self (Packard & Wooten 2013). Melumad and Meyer (2020) examine the degree of self-disclosure on social media, online restaurant reviews, and other manipulated settings by two approaches: an automated measure based on linguistic features, and human assessment relying on a Likert scale. For the linguistic measures, their study adopts the criteria of using first-person pronouns, references to family and friends, and words that convey negative emotions to judge self-disclosure texts (p.32). The second approach, human assessment, was conducted by asking MTurk participants to rate their agreement with a set of survey items. Based on a small training sample coded by MTurk participants, Yang et al. (2019) trained a machine learning (ML) model to estimate the amount of negative disclosure in their analysis. Consistent with this stream of research, we adopt linguistic measures to characterize disclosure messages in our study and train a ML model in the robustness check.

Some prior studies include emotional and cognitive related words in quantifying different types of disclosures (Gieselmann & Pietrowsky 2016; Ho et al. 2018; Shim et al. 2011). As noted in Morton (1978), the depth of disclosure is confounded with disclosure content, where factual disclosure is considered to be least intimate, cognitive disclosure represents an intermediate level of intimacy, and emotional disclosure represents the highest level. Ho et al. (2018) find that emotional disclosure is more effective in improving relational, emotional, and psychological outcomes than factual disclosure. To further understand the effects of mutual disclosures, we explore the depth of disclosure and measure the disclosure content from two perspectives: *cognitive disclosure* and *emotional disclosure*. Following the previous literature (e.g., Huang et al. 2017; Shim et al. 2011), we use cognitive disclosure to denote the content of disclosure that reflects cognitive processing, with the usage of causal, insight, and cognitive-related words (e.g., reason, know). Similarly, emotional disclosure indicates the content of disclosure that conveys affective processing, using emotion-related words (e.g., nice, hurt). Furthermore, we account for the valence of emotion and separate it into positive and negative emotional disclosure. As such, we focus on the intermediate (cognitive) and the highest (emotional) degrees of disclosure and consider other disclosure information (e.g., facts) as the baseline (Morton 1978). In this paper, we explore interactions between mutual disclosures in terms of intimacy consistency in disclosure content to enrich our understanding of disclosure interactions and depth in online group conversations.

Table 1. Review of Self-Disclosure Measures			
References	**Context / Data Collection**	**Measures of Self-Disclosure**	**Key Findings**
Barak and Gluck-Ofri (2007)	Forum messages from three support groups and three discussion groups	Expert Judges rate the degree to which each message disclosed personal information, thoughts, and feelings. Linguistic measures: length of writing and employment of **first-voice words (the number of such words as "I," "me," "mine," and so on)**	Self-disclosure in support forums was much higher than in discussion forums, in terms of both total number and type of disclosure; reciprocity of self-disclosure was evident, yielding positive correlations between the measures of self-disclosure in messages and responses to them.
Shim et al. (2011)	106 women with breast cancer wrote disclosive messages in bulletin-board-type online groups that provided services for information, social support, and decision making	Measure the **percentages of words conveying insights, negative emotion, and positive emotions** in messages based on LIWC dictionaries.	Disclosure of insights led to greater improvements in health self-efficacy, emotional well-being, and functional well-being. Disclosure of negative emotions did not have main effects on health outcomes, but weakened the unfavorable effect of breast cancer concerns on functional well-being.
Gieselmann and Pietrowsky (2016)	54 university students who suffer from symptoms of procrastination participated in a counseling experiment	Two methods by self-reported and LIWC measures: 1) Self-reported: "Please indicate now, to what extent you have revealed personal issues during counseling." 2) LIWC measure: a composite score of the categories **"I/first-person", "negative emotions" and "cognitive mechanisms (insightful and causal thinking)"**	Clients assigned to the chat (written)-based condition showed more self-disclosure reflected by their choice of words than in face-to-face. Both kinds of self-disclosure were associated with better treatment outcomes (i.e., decrease in procrastination) in the chat condition.
Kashian et al. (2017)	136 dyads of undergraduate students participated in a lab experiment to have an online conversation by chat channel	Count the number of **self-references (I, myself, me, my, mine, we, us, ourself, ourselves, and our)** by each participant as a self-disclosure.	Self-disclosure prompts receivers' interpersonal attributions, which led receivers to like their partners in computer-mediated communications (CMC).
Ho et al. (2018)	92 participants had an online conversation by Chatplat in an experiment (emotional vs. factual disclosure; with a chatbot vs. a person)	The disclosure type (emotional vs. factual) was manipulated in the experiment. Based on the chat transcripts, the authors measured disclosure intimacy into 3 levels: low - including objective facts about the situation; medium - including attitudes, thoughts, and opinions about the situation; and high - consisting of explicitly verbalized emotions and affect. And measured **cognitive reappraisal in disclosure process: usage of causal, insight-related, and positive emotion words** via LIWC categories.	The effects of emotional disclosure were stronger than factual disclosure on improving relational, emotional, and psychological outcomes. But this occurred regardless of whether participants thought they were disclosing to a chatbot or a person.
Morgan et al. (2019)	Consumer reviews for electronic devices from Amazon.com	LIWC measure: usage of words in the review text based on the **"Personal Concerns"** category	Personal disclosure adversely affects review persuasiveness.

Yang et al. (2019)	826,389 messages in the public channel and 105,213 private messages from 5,649 users of an online support community for cancer survivors	A small set of messages (1000) were coded by MTurk participants and then used to train machine learning regression models to predict/measure the amount of negative self-disclosure contained in each message.	Members of cancer support groups revealed more negative self-disclosure in the public channels compared to the private channels. Self-disclosure is reciprocated more in the private channel, compared to the public channel.
Melumad and Meyer (2020)	User posts on Twitter; restaurant reviews on TripAdvisor; experiments: participants wrote an upset personal experience; participants were required to describe a private product experience	Two methods by LIWC measures and human judgments: 1) The extent of word usage based on LIWC categories: **(a) first-person pronouns (e.g., “I,” “me”), (b) references to family and friends, and (c) words that convey emotionality—particularly negative emotions** 2) 1,925 MTurk participants rated a set of items on a seven-point scale, e.g., "To what extent does the writer focus on him/herself in this tweet?"; "To what extent does the writer reveal his or her personal feelings, thoughts, or opinions?"; "To what extent does the writer disclose personal information about him/herself?"; "To what extent does the writer disclose information that might make him/her feel emotionally vulnerable?"	Consumers tend to be more self-disclosing when generating content on their smartphone versus personal computer.

3. HYPOTHESES DEVELOPMENT

We conduct two studies to address our research questions. In Study 1, we evaluate how the overall breadth of disclosure from *other group members* and *a focal user* in OCG conversations jointly relate to the focal user's subsequent engagement. In Study 2, we consider the depth of disclosure and explore the interactions of mutual disclosures in terms of intimacy consistency of disclosure content. As stated, we examine three indicators of user engagement in OCG conversations: *promptness, positivity,* and *effort.* We use these three engagement outcomes as proxies of user liking for OCGs. In other words, users who like the OCGs more are believed to respond more promptly, express more positively, and exert greater effort in their chats with other members. Figure 1 illustrates the research framework.

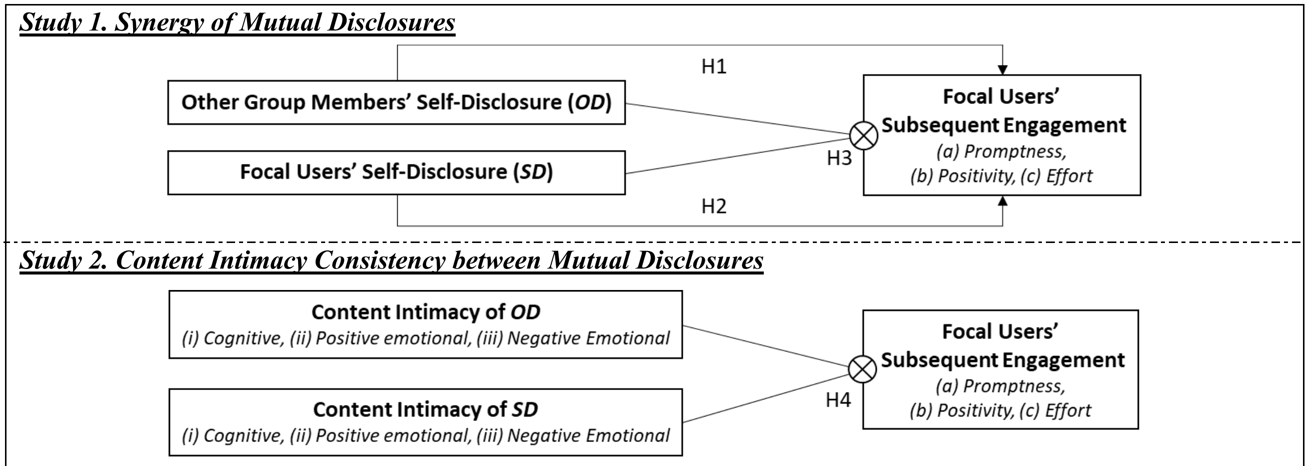

Figure 1. Research Framework

3.1. Synergy of Mutual Disclosures

Drawing upon the disclosure–liking framework of Collins and Miller (1994), people are inclined to like those who disclose self-related information to them (Effect 1). Altman and Taylor (1973) suggest that disclosure communicates the discloser's liking and desire to establish a more intimate relationship, which generates a positive assessment from the recipient. When applying this interpersonal link to the OCG context, the recipient (the focal user in our study) will like the disclosers (other group members in the OCG) more if the focal user receives more disclosures from them. Ajzen (1977) explains this positive relation from an information-processing perspective. That is, the recipient believes that those who disclose more are more trusting, friendly, and warm, and thus, tends to interact with the disclosers more. Therefore, in our case, we believe that a focal user who obtains more disclosures from other members in an OCG will exhibit greater liking towards the group, which will in turn generate quicker responses, more positive expression, and greater effort in their future engagement. We posit:

H1: Users who obtain more disclosure from other OCG members will have higher engagement (a) promptness, (b) positivity, and (c) effort in subsequent group conversations.

The effect of focal users' self-disclosure stands from the mechanism that people like their recipients more when they disclose more to them (Effect 3 in Collins & Miller 1994). Previous literature has shown that self-disclosure is a necessary component of mental health (Pennebaker et al. 1988). The act of self-disclosure is intrinsically rewarding (Tamir & Mitchell 2012) and positively associated with interpersonal solidarity (Wheeless 1976). Sharing one's self-experiences, whether positive or negative, can help improve mood (Berger 2014), especially among the persons who have similar background and problems (Shim et al. 2011). Therefore, a focal user who has disclosed more about themselves in the OCG is likely to have stronger liking towards the recipients and the group. As a result, they will be more willing to engage in future group conversations through prompt replies, positive expression, and significant effort. We thus posit:

H2: Users who disclose more about themselves will have higher engagement (a) promptness, (b) positivity, and (c) effort in subsequent group conversations.

Moreover, we argue that there is a complementary relationship between mutual disclosures from other group members and the focal user. Previous studies have verified the reciprocity of disclosure, such that the amount of one's self-disclosure will increase with more disclosure from others (Jourard 1959). People tend to disclose more when others are warm and receptive than when they are negative or cold during conversations (Heller 1972). More importantly, as the disclosure process evolves, the overall intimacy among people will be enhanced (Morton 1978). In this sense, obtaining more disclosure from each other will foster group cohesion, thereby enhancing users' attachment to the group, and in turn, their engagement in subsequent group conversations. As a result, we can observe positive interactions between mutual disclosures on the focal user's later engagement. Therefore, we posit the following hypotheses:

H3: There are positive interactions between mutual disclosures on focal users' engagement (a) promptness, (b) positivity, and (c) effort in subsequent group conversations.

3.2. Content Intimacy Consistency between Mutual Disclosures

We further explore the effects of mutual disclosures in terms of content intimacy. According to a review by Kleinke (1979), people feel obligated to respond to a personal disclosure with equal intimacy. Previous psychological theory has also highlighted the importance of feeling understood in interpersonal relationships (Reis et al. 2017). If disclosers perceived that they can be understood by recipients, this would bring emotional, relational, and psychological benefits to the disclosers (Ho et al. 2018). From this viewpoint, we focus on the content intimacy consistency between mutual disclosures from the focal user and other group members. We hypothesize the interactions at different intimacy levels.

Cognitive Disclosure – represents an intermediate level of intimacy. People sometimes seek opinions to reduce cognitive dissonance (Festinger 1957) because they are uncertain about situations (Berger 2014). In OCG conversations, users discuss and comment on the problems they have in common to acquire helpful information from each other. Talking to others helps them cope with their problems, confirm their own judgment, and reduce their feelings of doubt (Engel et al. 1993). In this case, conversations with consistent cognitive discussions can synchronize users' attention and help them gain the necessary information. This can promote quicker responses, more positive expression, and greater effort in users' future conversations. On the other hand, users might not be able to obtain valuable information from conversations without intensive cognitive interactivity. As a result, users might be demotivated to engage actively in future discussions.

Positive and Negative Emotional Disclosure – represents the highest level of intimacy. People share emotions in communication to foster emotion regulation. Expressing positive emotions helps to re-consume pleasurable feelings (Rimé 2009). Gable et al. (2004) find that positive emotions can be enhanced by communicating positive events with others. Therefore, when OCG users share, read, or compliment pleasant experiences with each other, their positive feelings will be elevated. On the other hand, people express negative emotions to seek social support or simply to vent (Berger 2014). However, it is unclear whether complaining together in conversations may relieve negative emotions or elicit even worse outcomes. Previous research has suggested that people like those who share similar views (Byrne 1969; Cozby 1973). Barsade and Gibson (2007) find that when members in organizations share emotional stories, they are more likely to perceive similarities to each other, thus improving group cohesiveness. Likewise, Wang et al. (2008) study the relationship between perceptions of similarity and deep involvement in online health discussion groups. They find that when users detect similarities with online partners (such as having similar negative experiences) through written message cues, they idealize these partners and develop intimate relationships. In this sense, conversations with shared emotions, regardless of positive or negative, will help users feel better, foster their perception of the group and group members' attraction, and thus improve their engagement in the future. By contrast, users might feel disappointed and be demotivated to engage in future conversations if their emotions cannot be spread over.

Combining the above, we posit the following hypotheses:

H4: The interaction effects of mutual disclosures on focal users' engagement in subsequent group conversations will be positive when the mutual disclosures are consistent in (i) cognitive, (ii) positive emotional, and (iii) negative emotional content, while the interactions will be negative when the mutual disclosures are inconsistent in these aspects.

4. DATA AND VARIABLES

4.1. Research Setting and Data

We obtain the data of this paper from Kidswant (haiziwang.com), a leading online and offline retailer in China that sells a wide variety of maternal and infant supplies, including diapers, infant formula, equipment, toys, baby clothes, and household items (similar to Babies'R'Us). By the end of 2022, this retailer has more than 508 offline stores nationwide to serve about 53 million members, where 49.97% of revenue is from online channels. The customers are mainly young parents with children under four years old. As the consumption of maternal and baby products usually requires professional advice, the retailer assigns each registered customer, no matter from online or offline channels, to a specific brand manager for follow-up services. To achieve the service objective efficiently, each brand manager organizes the customers through OCGs built on WeChat, where the brand manager serves as the host of the OCGs and the group users are the customers.[3] These OCGs are dedicated to providing instant consulting services, and facilitating discussions and interactions among the groups of customers. Brand managers can provide maternal and baby care knowledge to address customers' queries. Customers can also share parenting experiences with each other. Compared to social media channels, the OCGs are particularly valuable for this retailer to reach and manage customers with higher accessibility, provide an environment to engage customers, and in turn, foster stronger customer loyalty.

The retailer runs more than 50,000 OCGs nationwide to manage registered customers, with each group including no more than 500 members. In this study, we randomly select 80 groups with customers from one city as our sample and extract all the messages in these groups from May 2017 to November 2018. We focus on the groups with relatively active communication and exclude 12 groups with insufficient information, which either had fewer than 100 messages or the duration of conversations was shorter than 1 month. There is a total of 683,254 text messages during our observation window in the remaining 68 groups. Among them, 646,337 messages are sent by 14,386 customers, and the remaining messages are from brand managers.

4.2. Variables

4.2.1. Self-Disclosure from Different Sources.

To understand users' self-disclosure in conversations, we first group the messages into conversation threads within each OCG. A conversation is identified by an initiating message followed by other messages concerning a similar topic. In contrast to most UGC platforms (e.g., social media pages and discussion communities), where the initial message and reply messages are well-organized in one thread, conversations over OCGs are interleaved with each other (see Table 2 for an example). Thus, it is necessary to disentangle the interleaved text conversations and allocate each message to a specific conversation in our context. We employ a context-based message expansion algorithm by Wang and Oard (2009) for disentanglement of interleaved text conversations. The main idea is to exploit temporal, author, and social aspects of the conversations to build context-sensitive representations for each message, and then cluster the messages into conversations based on the similarity of their new representations.[4] A total of 40,582 conversations were eventually identified from our sample.

Table 2. An Example of Conversation Grouping

Time	Sender	Original Message (in Chinese)	Message Translation	Conversation ID
2017/5/27 7:05 PM	Customer 1	问一下群里的宝妈，你们娃多大开始坐的？	I have a question for mothers here: how old did your baby start to sit?	1
2017/5/27 7:06 PM	Customer 2	我们出月子就坐了啊。	My kid started to sit one month after birth.	1
2017/5/27 7:18 PM	Customer 3	有人用过 XX 奶粉吗？388 一罐	Has anyone used XX milk powder? A can costs $388.	2
2017/5/27 7:19 PM	Customer 3	这么早啊！太早坐对宝宝腰不好吧。	That early! Sitting up too early may not be good for your baby's waist.	1
2017/5/27 7:24 PM	Manager	每个宝宝的生长发育速度不同，一般来说 6-7 个月开始会坐。	Each baby grows at a different rate, but generally 6-7 months should be common.	1
2017/5/27 7:26 PM	Manager	@Customer 3 这款奶粉针对容易长湿疹的宝宝，最近在门店有买六送一的折扣哦。	@Customer 3 this milk powder targets the babies who are prone to eczema. It has a buy 6 get 1 for free promotion in the store now.	2
2017/5/27 7:28 PM	Customer 2	我的意思不是完全 90 度坐直，是有点斜度的躺。	I didn't mean sitting upright at exactly 90 degrees. I meant lying slightly inclined.	1
2017/5/27 7:43 PM	Customer 1	哦~因为我们躺平就闹！让他坐起来就不闹了！	I see ~ because my baby cries whenever he is flat on bed. He stops as soon as we let him sit up!	1

[3] The usage of WeChat has full coverage among the sample users. The brand managers contact the customers through WeChat and add them to OCGs. If the customers do not want to use the OCGs, they can drop out of the groups freely. We did not observe frequent variations in group size.

[4] We manually labeled 3000 messages and trained the model. We evaluated the model performance based on one-to-one accuracy and loc3 metrics (Elsner & Charniak 2008). One-to-one accuracy describes how well we can extract whole conversations intact and measures the percentage of overlaps (messages grouped in the same conversation as the ground truth) out of the messages in a conversation. Loc3 is the local agreement average of whether those three consecutive messages are assigned consistently by the ground truth and the detected results. Both metrics achieved values above 0.8, suggesting good model performance.

2017/5/27 8:05 PM	Customer 4	XX 奶粉我们在吃，当时也是因为娃长湿疹，医生建议买的。	We are eating XX milk powder. As our baby had eczema before, the doctor suggested buying it.	2
2017/5/27 8:09 PM	Customer 3	@Manager @Customer4, 谢谢！	@Manager @Customer4, thanks a lot!	2

We use the same linguistic measures as Melumad and Meyer (2020) to identify the *disclosure messages,* which should contain at least one of the following linguistic categories in the text: (1) first-person pronouns (e.g., "I", "my", "we", "our") and words with similar meanings in Chinese, (2) "family" and "friends" related words, and/or (3) negative emotion words based on the Linguistic Inquiry and Word Count (LIWC) psycholinguistic dictionaries (Pennebaker et al. 2015). We use the Jieba[5] toolkit for Chinese word segmentation and apply the filter criteria to select disclosure messages. As a result, 227,680 messages meet the criteria and are marked as disclosure messages. In the main analyses, we report the results based on the criteria of these linguistic features. We also train a ML model to classify the disclosure messages. The results based on ML predictions are reported in the Additional Analyses part.

Based on the conversation recognition and the classification of disclosure messages, we construct mutual disclosures *within each conversation* by disentangling the disclosure sources, namely, disclosure from other OCG members (*OD*) and disclosure from a focal user (*SD*). Previous studies have considered the breadth of self-disclosure as the number of self-related statements made during an interaction (Collins & Miller 1994). Later studies divide the absolute number by the total volume of writing to account for differences in individual activity levels (e.g., Pennebaker et al. 1997; Shim et al. 2011). In the same manner, using each focal user and their conversation as a unit, we calculate the word count ratio of disclosure messages to all messages from *other members*, and the word count ratio of disclosure messages to all messages from the *focal user* in the same conversation.[6] We then construct the breadth of *OD* and *SD* on a daily basis, by averaging the corresponding disclosure amount from other members and the focal user, respectively, over all the conversations where the focal user has participated on day *t*. Noting that OCG members may use the "@" sign to specify a message target. To achieve a more precise measurement, we exclude the disclosure messages from other members that contain @ but the target is not the focal user in the calculation of *OD*.[7] The amount of SD can be zero when focal users do not disclose any personal information in their messages.

4.2.2. Cognitive and Emotional Disclosure.

We distinguish cognitive and emotional disclosures. Consistent with prior work (e.g., Shim et al. 2011), LIWC psycholinguistic dictionaries are adopted to measure disclosure content. In particular, we use the dictionaries of cognitive/insight/causation, positive emotion, and negative emotion to obtain the respective usage proportions of cognitive words, positive emotional words, and negative emotional words in each disclosure message. Based on this, we derive the count of each word type. We then calculate the breadth of cognitive (Cog), positive emotional ($PosEmo$), and negative emotional ($NegEmo$) disclosures as the ratios of the corresponding words in disclosure messages to the words in all messages in each conversation from other members and the focal user, respectively. Similarly, we further average the disclosure amount over all conversations that the focal user has been involved in on day *t*.

4.2.3. Engagement in OCGs.

As stated, we characterize user engagement in OCGs in three aspects: *promptness, positivity,* and *effort*. As we cannot observe users' degrees of liking toward OCGs directly from our data, we use these three variables as the proxies to represent user liking for OCGs. Particularly, to quantify engagement promptness, we first calculate the average time difference in minutes of a focal user's reply to a previous message in each conversation and aggregate these values at the day level by averaging over the conversations. In this case, the smaller time difference indicates quicker responses. Further, to represent promptness in the same direction as its conceptual meaning, we make a linear transformation using the maximum time difference of the whole dataset minus the focal user's time difference on the day. By doing this, a higher value of this variable means a more prompt response. When promptness equals zero, it indicates that the users are engaged at the lowest level in terms of response speed.[8] Engagement positivity is quantified as the average count

[5] https://github.com/fxsjy/jieba

[6] We remove stop-words, emoji, pictures, maps, and voice messages to focus only on textual information, and use the Jieba toolkit to calculate the word count of each message. Some unique words in our research context, such as the retailer's brand and product names, are incorporated to improve the segmentation accuracy.

[7] We thank an anonymous reviewer for this suggestion. The function of @ is mainly used for reminding a person in the group to read the messages, but the messages are still visible to the entire group. Thus, for the messages sending from a focal user (*SD*), we did not consider whether the messages point to a specific recipient or all group members.

[8] The user with the maximum time difference received a zero promptness value after linear transformation. We consider this record as an outlier because the maximum time difference is 1098.54 minutes in our sample (longer than 18 hours). Therefore, we believe this

difference between positive emotion words and negative emotion words of a focal user's daily messages (Goh et al. 2013). The positivity variable could be negative when there are more negative emotional words than positive ones, and it equals zero when the counts of positive and negative emotional words are equal or there are no emotional words in messages. Engagement effort is measured by the average length (i.e., total count of words divided by the number of messages) of a focal user's daily messages (Pu et al. 2020). Since we calculate these measures for users who have sent messages on day *t,* there are no missing values of engagement at the day level.

To formulate the dependent variables, we sum up the daily engagement measures over the subsequent *seven calendar days*. This approach is adopted because liking is not a transient state. By aggregating the engagement measures over a fixed period, we can capture users' relatively stable affection, as evidenced by their engagement behavior in the future. In addition, this approach can more or less eliminate the influence of occasional needs on users' self-disclosure and immediate follow-up engagement. In cases where users do not have records in the subsequent seven calendar days, we assign their dependent variables as zero, indicating no engagement. Therefore, this enables us to evaluate the overall effects on users' engagement tendency and intensity, and avoid potential sample selection issues. In the robustness checks, we exclude the records of the users whose engagement values are missing in the subsequent seven calendar days and reevaluate the relationships. Additionally, we adjust the time window of subsequent engagements to three days. Following prior work (e.g., Pu et al. 2020), we also measure user engagement by the total number of words or messages. More details of the alternative measures and their results are reported in Additional Analyses.

4.3. Summary Statistics

We focus on user (customer) engagement and construct an unbalanced panel dataset at the individual-day level where a focal user *i* has sent at least one message on day *t*. Each user in our data belongs to one OCG. We code the independent variables for each user *i* on day *t*. The dependent variables are the sum of user *i'*s engagement measures in the subsequent calendar week (seven days) since day *t+1*. The final dataset includes 97,832 observations and Table 3 lists the descriptive statistics of the main variables. It shows that the average reply time difference (the interim measure before transformation to the promptness variable) is 11.4 minutes on a daily basis. The average engagement positivity in a week is 0.35, suggesting that the overall sentiment of user messages in OCG conversations is neutral. In terms of engagement effort, the mean value of message length in a week is about 41.4 words. For the disclosure variables, the mean value of self-disclosure from focal users is 0.573, supporting that users in OCGs have a high level of disclosure. This is consistent with the study of Melumad and Meyer (2020) that about half of the communication in their context is self-disclosure oriented. The mean value of disclosure from other OCG members is slightly lower (0.418). This is probably due to a low disclosure rate from brand managers. We will provide further discussion in this regard in additional analyses. Among focal users' self-disclosure messages, cognitive disclosure has the highest percentage (2.7%), and the average of positive and negative emotional disclosures are similar (2.3% and 2.2%). The statistics of disclosure messages from other OCG members show a similar pattern. Their average level of cognitive disclosure (2.1%) is higher than the emotional disclosures (1.6% and 1.8%). Although the OCG context provides a relatively private and anonymous environment, our data suggests that users still prefer to express objective opinions, compared with emotions.

Table 3. Descriptive Statistics of Main Variables

Variable	Description	Mean	S.D.	Min	Max
Eng_ Promptness	Transform the daily *time difference*, and sum the values in the subsequent week	1272.51	1802.79	0	7687.12
(Time difference)	Average daily time difference in minutes of a focal user's reply to a previous message in each conversation	11.38	32.16	0	1098.54
Eng_ Positivity	Average count of *positive emotional words minus negative emotional words* that a focal user has chatted daily, and sum the values in the subsequent week	0.35	1.46	-30.78	36
Eng_Effort	Average *length* of messages that a focal user has chatted daily, and sum the values in the subsequent week	41.40	91.78	0	3193.95
Eng_Word	Total number of *words* that a focal user has chatted in the subsequent week	181.8	1780.78	0	153341
Eng_Msg	Total number of *messages* that a focal user has chatted in the subsequent week	7.166	26.861	0	986
SD	Average word-count ratio of a focal user's *self-disclosure* messages to all their messages in the conversations on day *t*	0.573	0.391	0	1.000

user was highly reluctant to reply and treat him/her as conceptually equivalent to those who did not reply.

CogSD	Average word-count ratio of *cognitive* words in a focal user's disclosure messages to all their messages in the conversations on day *t*	0.027	0.043	0	0.667
PosEmoSD	Average word-count ratio of *positive emotional* words in a focal user's disclosure messages to all their messages in the conversations on day *t*	0.023	0.044	0	1.000
NegEmoSD	Average word-count ratio of *negative emotional* words in a focal user's disclosure messages to all their messages in the conversations on day *t*	0.022	0.049	0	1.000
OD	Average word-count ratio of *other members' disclosure* messages to all their messages in the conversations where the focal user chatted on day *t*	0.418	0.281	0	1.000
CogOD	Average word-count ratio of *cognitive* words in other members' disclosure messages to all their messages in the conversations where the focal user chatted on day *t*	0.021	0.022	0	0.500
PosEmoOD	Average word-count ratio of *positive emotional* words in other members' disclosure messages to all their messages in the conversations where the focal user chatted on day *t*	0.016	0.022	0	0.500
NegEmoOD	Average word-count ratio of *negative emotional* words in other members' disclosure messages to all their messages in the conversations where the focal user chatted on day *t*	0.018	0.021	0	0.667

We evaluate the potential issue of multicollinearity based on variance inflation factors for all the independent variables. All values are found to be below the commonly accepted threshold of 10 (Kennedy 2003), indicating that multicollinearity is not a concern in our models. We standardize the disclosure variables for model estimation.

5. ANALYSES AND RESULTS

5.1. Propensity Score Matching

Considering the potential differences between disclosing and non-disclosing users in various aspects, we first apply matching approaches to find a matched sample regarding focal users' self-disclosure. We run a logit model to match the non-zero self-disclosure users and those with zero self-disclosure (i.e., treated or not) every day by propensity score matching (PSM) (Dehejia & Wahba 2002). For this purpose, we use the group and individual characteristics measured prior to that day as the covariates. We include the number of group messages to capture group activeness, the number of group members to indicate group size, and the number of conversations the focal user initiated to account for the user's query needs. We also consider users' historical engagement by including the cumulative number of messages from the focal user prior to the current day in the regression. Time-fixed effects are added to balance the matched sample. For each observation that was treated, we find a nontreated observation that is highly similar in terms of its treatment model score, using the nearest neighbor matching method. Table 4 provides the results of balance checks for the key covariates in the PSM. The results show that these individual and group characteristics are not statistically different at the 1% level between the treatment and control group after matching.[9]

Table 4. Balance Checks for PSM

Variable	Matched	Mean (Treated)	Mean (Control)	%bias	t	p>t
# of group messages	Before	126.74	120.04	3.70	4.50	0.00
	After	126.50	128.03	-2.00	-2.03	0.04
ln (# of group members)	Before	5.55	5.62	-13.00	-16.37	0.00
	After	5.55	5.55	-0.30	-0.42	0.67
# of conversations a focal user initiated	Before	0.50	0.15	70.60	79.54	0.00
	After	0.48	0.48	0.60	0.93	0.35
ln (# of cumulative messages from a focal user)	Before	6.97	6.23	36.90	48.92	0.00
	After	6.95	6.95	0.20	0.38	0.71

5.2. Model-Free Evidence

Before we implement regression models, we visualize the comparisons of subsequent user engagement under different disclosure levels using the matched sample. Figure 2 plots the mean values of *Engagement Promptness,*

[9] In addition to PSM, we also conducted coarsened exact matching (CEM) as an alternative matching approach. The results remain consistent.

Positivity, and *Effort* at high (> Mean+0.5Std) and low (< Mean-0.5Std) disclosures. As can be seen, the users who received more disclosure from other members replied faster, engaged more positively, and wrote longer messages in the subsequent week than those who received less disclosure from others. Similarly, the users who had higher self-disclosure engaged with quicker responses, higher positivity and more effort in the subsequent week compared with those who had lower self-disclosure. The descriptive evidence supports that mutual disclosures (from others and self) are positively related to subsequent engagement.

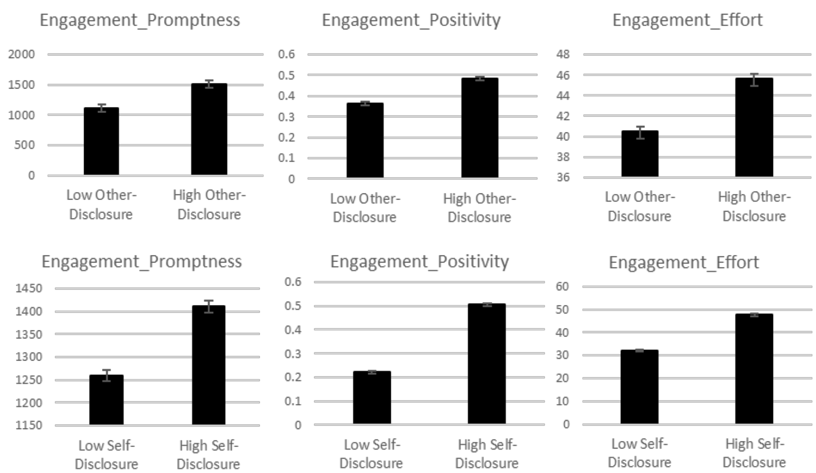

Figure 2. Model-Free Evidence of Disclosure and Engagement

5.3. Study 1 - Synergy of Mutual Disclosures

In this section, we examine the main and interaction effects of mutual disclosures using the matched sample by the following regression model:

$$\sum Y_{i,t+1\sim 7} = \beta_0 + \beta_1 OD_{i,t} + \beta_2 SD_{i,t} + \beta_3 SD_{i,t} \times OD_{i,t} + Controls_{i,t} + u_i + \tau_t + \varepsilon_{it} \qquad (1)$$

The dependent variables are the sum of engagement values in the subsequent seven calendar days. We take a natural logarithm transformation of promptness in the regression. In addition to the main variables of interest (i.e., *OD* and *SD*), we add a series of controls related to focal users, brand managers, and chat groups. We include four focal user-related variables: historical engagement measured as the number of words that the user has typed in the group up to day *t*,[10] the number of days since the user sent the first message until day *t*, the number of conversations that the user initiated on day *t*, and the number of conversations that the user joined and were initiated by a question on day *t*.[11] We control two variables related to brand managers: skill level provided by the HR department of the retailer, reflecting four ordinal levels of a brand manager's ability, and tenure, measured by the number of months since they were hired, to account for brand manager seniority. For each chat group, we account for group size, measured by the number of group members on day *t*, because community size might affect content generation (Zhang & Zhu 2011). We also consider group-level activeness, which is measured by the total number of messages in the group on day *t*. We include fixed effects in the models to control for unobserved individual and group differences that cannot be captured by matching. Besides, we include month dummies to control for unobserved time trends.

Table 5 reports the results of the regressions. In Columns (1)-(3), we examine the main relationships between *OD*, *SD* and subsequent engagement promptness, positivity, and effort, respectively. The results show that disclosure from other members is significantly associated with focal users' subsequent engagement in all three aspects. H1 is supported. When holding all other variables constant, engagement promptness, positivity, and effort in the subsequent week would increase by 15.6%, 0.028, and 1.434, respectively, with a one-unit (i.e., one standard deviation from the mean) increase in other members' disclosure. Meanwhile, the coefficients of focal users' self-disclosure are also significant, and more self-disclosure is associated with quicker responses, more positive expression, and greater effort in their subsequent engagement. Thus, H2 is supported. When self-disclosure increases by one unit, *ceteris paribus*, focal users' engagement promptness, positivity, and effort would increase by 9.6%, 0.022, and 1.241. In comparison, other members' disclosure in

[10] We also measure past engagement behavior as the number of messages, and the results are robust.

[11] We classify a message as a question by checking the presence of question marks or any of the question leading words such as "why", "what", "which", and "how" in the Chinese language.

group dialogues is more effective in motivating focal users' subsequent engagement.

Furthermore, we examine the interaction relationships in Columns (4)-(6). The interaction terms between mutual disclosures are significant for engagement promptness (Coef. = 0.051) and positivity (Coef. = 0.017), and marginally significant for engagement effort (Coef. = 0.550). In support of H3, focal users' subsequent engagement in the OCGs will be further enhanced when they read more disclosures from each other. The results verify the necessity of differentiating the source of disclosures in group conversations, and show the significant synergy of mutual disclosures in facilitating user engagement.

Table 5. Results of Overall Mutual Disclosures

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
OD	0.156***	0.028***	1.434***	0.145***	0.025***	1.331***
	(0.025)	(0.005)	(0.324)	(0.026)	(0.005)	(0.331)
SD	0.096***	0.022***	1.241***	0.087***	0.019***	1.120***
	(0.024)	(0.005)	(0.306)	(0.024)	(0.005)	(0.310)
SD×OD				0.051**	0.017***	0.550*
				(0.024)	(0.005)	(0.313)
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
_cons	-0.419	-0.173	-44.453***	-0.401	-0.165	-43.755***
	(0.470)	(0.105)	(6.613)	(0.470)	(0.105)	(6.612)
N	90090	90090	90090	90090	90090	90090
Adjusted R^2	0.038	0.030	0.168	0.038	0.030	0.169

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

5.4. Study 2 - Content Intimacy Consistency

We further examine disclosure content and explore the interactions of mutual disclosures regarding content intimacy consistency with the following model:

$$\sum Y_{i,t+1\sim 7} = \beta_0 + \sum\beta_{1p}OD_{i,t,p} + \sum\beta_{2p}SD_{i,t,p} + \sum\beta_{3p,q}SD_{i,t,p} \times OD_{i,t,q} + Controls_{i,t} + u_i + \tau_t + \varepsilon_{it} \quad (2)$$

Here we regress engagement outcomes on the content measures of disclosure with a focus on the pairwise interactions of multiple disclosure content between focal users and other members. We use $p, q \in \{Cog, PosEmo, NegEmo\}$ to represent different content aspects. $\beta_{3p,q}$ represent the 9 (3x3) coefficients of our interest. In addition, we add the main effect of each disclosure content from other members and the focal user, and use the same model specifications with the same set of controls as in Study 1 in the regression model.

The results of interaction terms are presented in Table 6 and reveal multifaceted associations with engagement outcomes. As shown in Columns (1)-(3), when mutual disclosures are consistent in content intimacy, their interactions are overall significant and positive for all types of disclosure content. In particular, we find significant interactions between mutual cognitive disclosures regarding positivity and effort of focal users' subsequent engagement, and the interaction is marginally significant in terms of response time. Mutual disclosures with positive content are significantly related to engagement outcomes in all three aspects. Interestingly, mutual disclosures with negative content are also significantly associated with higher engagement positivity. Our results suggest that users prefer to share emotions in the OCG context and tend to respond more promptly, engage more positively, and send longer messages when their feelings can be spread over.

Regarding the interactions of mutual disclosures with inconsistent content intimacy, the results suggest mixed patterns for different disclosure content (Columns (4)-(6)). When focal users' cognitive contents are mixed with other members' positive emotions in conversations, focal users' subsequent engagement would be enhanced (Coef. = 0.061 for promptness, Coef. = 0.025 for positivity, Coef. = 0.576 for effort). In these cases, other members' appreciation of focal users' cognitive disclosure would encourage them respond faster, engage more positively, and with greater effort in the future. By contrast, focal users' engagement would be discouraged if other members send negative messages in their cognitive sharing (Coef. = -0.173 for promptness, Coef. = -0.050 for positivity, Coef. = -1.894 for effort). H4(i) are thus partially supported.

Users do not like different disclosure content from other members when they send positive messages. The interactions between focal users' positive emotional disclosure and other members' disclosure with either cognition or negative emotions are significantly negative (Coef. = -0.093 and -0.113 for promptness, Coef. = -0.049 and -0.080 for positivity, Coef. = -1.150 and -2.410 for effort). When focal users want to express positive emotions but others are not at the same wavelength, their subsequent engagement will be undermined, supporting H4(ii).

The interactions of inconsistent mutual disclosures are not always negative when focal users send negative messages. The interaction of focal users' negative emotional disclosure and other members' cognitive disclosure shows a significantly positive association with subsequent engagement positivity (Coef. = 0.026), and marginally positive associations with promptness (Coef. = 0.034) and effort (Coef. = 0.541). The results suggest that cognitive opinions may help users obtain useful information and recover from their negative emotions, and focal users tend to engage in subsequent conversations with quicker responses, higher positivity, and more effort. However, if other members send positive messages in focal users' negative sharing, it will discourage focal users' subsequent engagement (Coef. = -0.128 for promptness, Coef. = -0.045 for positivity, Coef. = -1.802 for effort). H4(iii) are partially supported.

Table 6. Results of Mutual Disclosures Regarding Content Intimacy

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
Disclosure Interaction with Consistent Content Intimacy						
CogSD×CogOD	0.028*	0.050***	0.510**	0.035*	0.081***	0.645**
	(0.017)	(0.004)	(0.244)	(0.019)	(0.004)	(0.274)
PosEmoSD×PosEmoOD	0.193***	0.022***	2.013***	0.249***	0.024***	2.929***
	(0.016)	(0.004)	(0.231)	(0.017)	(0.004)	(0.241)
NegEmoSD×NegEmoOD	0.028*	0.021***	0.418*	0.042**	0.020***	0.630**
	(0.017)	(0.004)	(0.243)	(0.019)	(0.004)	(0.270)
Disclosure Interaction with Inconsistent Content Intimacy						
CogSD×PosEmoOD				0.061***	0.025***	0.576**
				(0.019)	(0.005)	(0.276)
CogSD×NegEmoOD				-0.173***	-0.050***	-1.894***
				(0.021)	(0.005)	(0.303)
PosEmoSD×CogOD				-0.093***	-0.049***	-1.150***
				(0.021)	(0.005)	(0.307)
PosEmoSD×NegEmoOD				-0.113***	-0.080***	-2.410***
				(0.020)	(0.005)	(0.297)
NegEmoSD×CogOD				0.034*	0.026***	0.541*
				(0.020)	(0.005)	(0.287)
NegEmoSD×PosEmoOD				-0.128***	-0.045***	-1.802***
				(0.021)	(0.005)	(0.307)
Main Effects	Included	Included	Included	Included	Included	Included
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
N	90090	90090	90090	90090	90090	90090
Adjusted R^2	0.369	0.115	0.188	0.370	0.118	0.189

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6. ADDITIONAL ANALYSES

In this section, we first conduct a controlled experiment to verify the relationships between disclosure and engagement and the mediation effect of liking. We also explore the distinct roles of peer users and group hosts, and check robustness by a series of analyses.

6.1. (A) Controlled Experiment

Considering that the disclosure variables and engagement positivity/effort are all measured through message content, there might be spurious correlations due to the same information source.[12] To further check the effects of disclosure on engagement positivity/effort, we conduct a controlled experiment. Three hundred and two participants were recruited through an online survey platform[13] and were randomly assigned to conditions in a 2 (OD degree: high vs. low) * 2 (SD degree: high vs. low) between-subjects design. In the experiment, we mimic conversation scenarios in an OCG using the real messages from our observational data. We manipulate the degree of other users' disclosure and a focal user's disclosure in the conversation. Specifically, participants in the high disclosure condition read the messages which are more self-focused, more prominently referred to family, and contain more emotional words. An example message is, "Our baby cannot sleep well at night because of eczema, and it makes us unable to sleep either. It's really tormenting." By contrast, participants in the low disclosure condition read the messages which are more objective, for example, "Babies with eczema cannot sleep well at night, and it will be very difficult for their parents to sleep either." All respondents were told that they were the focal user ("I") who chatted with other members ("O1&O2") in this group, and were asked to rate a set of items indicating: 1) how much they like this chat group and group members (i.e., liking); 2) how likely they will chat positively in the group in the future (i.e., engagement positivity); and 3) how likely they will make great effort to chat in the group in the future (i.e., engagement effort) on a 7-point scale (from 1="not at all" to 7="very much"). These measures serve as the dependent variables. In addition to engagement positivity and effort, we measure user liking directly in the experiment. Moreover, we check the manipulations by asking respondents, "To what extent did the person "I" (or "O1&O2") disclose personal information about him/herself (or themselves) in this conversation?" The conversation examples and measurement details are provided in Appendix A. We use the average value of the measurements of each construct in the analyses.

The manipulation checks show significant difference between the high and low groups of the two disclosure factors (OD high=5.934 vs. OD low=4.666, p<0.001; SD high=6.063 vs. SD low=5.118, p<0.001). The results of ANOVA show that the main effects of both OD and SD are significant on focal users' liking (OD high=5.953 vs. OD low=5.548, F=24.391, p<0.001; SD high=5.992 vs. SD low=5.509, F=34.538, p<0.001); engagement positivity (OD high=6.064 vs. OD low=5.708, F=15.305, p<0.001; SD high=5.992 vs. SD low=5.780, F=5.4, p=0.021); and engagement effort (OD high=6.188 vs. OD low=5.781, F=19.820, p<0.001; SD high=6.153 vs. SD low=5.816, F=13.607, p<0.001). Moreover, the interaction effects between OD and SD on focal users' liking toward the group and engagement effort are significant in the ANOVA results (liking: F=6.739, p=0.01; effort: F=5.150, p=0.024). The interaction effect on engagement positivity is marginal (F=3.478, p=0.063). Figure 3 illustrates the effects of focal users' self-disclosure under high vs. low other members' disclosure regarding the three outcomes. These results provide further support for the relationships between mutual disclosures and user engagement in OCGs.

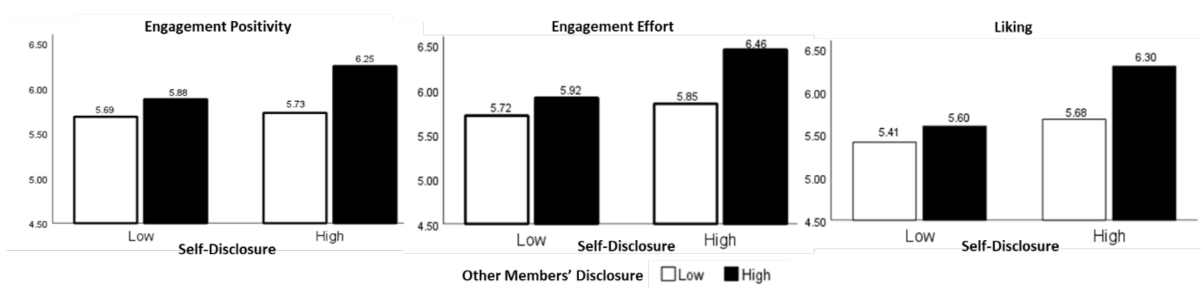

Figure 3. Effects of Mutual Disclosures on Liking and Engagement Positivity/Effort

6.1.1. Mediation Effect of Liking.

As noted in our theoretical development, mutual disclosures in previous dialogues can promote users' subsequent engagement because disclosures lead to more liking based on the disclosure–liking framework (Collins & Miller 1994), and users who like the community tend to engage with positive emotions and effort. In other words, liking plays a mediating role in the relationship between disclosure and engagement. To test this mechanism completely, we examine the mediation of liking using the data from the experiment. Table 7 shows the results of mediation analysis following the three steps by Baron and Kenny (1986). The results in Step 3 show that liking is a significant predictor of engagement. The coefficients of other members' disclosure are still significant but greatly reduced compared to their coefficients in Step 1, and the coefficients of focal users' self-disclosure become non-significant. Therefore, the effect of other members' disclosure is partially mediated by focal users' personal liking, suggesting that disclosure information from

[12] Engagement promptness is measured by time dimension, so this concern is not applicable.
[13] The survey platform is: https://www.credamo.com/

others has an extra effect on focal users' subsequent engagement. However, the effect of focal users' self-disclosure on engagement is fully mediated by their liking toward the group. The findings of mediation analysis confirm our theoretical argument that disclosure facilitates user engagement in group conversations through the mechanism of liking.

Table 7. Mediation Analysis

	Step 1		Step 2	Step 3	
Variables	Positivity	Effort	Liking	Positivity	Effort
OD	0.238***	0.252***	0.214***	0.0877***	0.122***
	(0.0380)	(0.0385)	(0.0348)	(0.0310)	(0.0341)
SD	0.200***	0.225***	0.281***	0.00292	0.0532
	(0.0382)	(0.0387)	(0.0349)	(0.0323)	(0.0357)
Liking				0.702***	0.611***
				(0.0487)	(0.0537)
Gender	0.0260	0.130	0.00498	0.0225	0.127*
	(0.0855)	(0.0866)	(0.0783)	(0.0656)	(0.0724)
Parenting	0.172	0.0711	0.0198	0.158	0.0589
experience	(0.159)	(0.161)	(0.145)	(0.122)	(0.134)
Constant	3.340***	3.254***	3.034***	1.211***	1.401***
	(0.327)	(0.331)	(0.299)	(0.291)	(0.321)
Observations	302	302	302	302	302
R-squared	0.206	0.234	0.286	0.534	0.467

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6.2. (B) Disclosure from Peer Users vs. Group Host

The sources of disclosure from other members include peer users (customers) and the group host (brand manager) in each group. Previous literature has investigated the nuanced role of managerial response to user posts on public platforms; however, the effect may not be positive in many cases. For instance, Ma et al. (2015) classify users' messages on Twitter into compliments and complaints, and find that firms' responses to user complaints may even elicit more complaints later on. Wang and Chaudhry (2018) study managers' responses to customer reviews on travel platforms and find that the responses to positive reviews might be treated as a premeditated means of promotion and thus have a negative effect on subsequent review generation. Chen et al. (2019) show that although managerial responses can positively affect the volume of subsequent customer reviews, the effect on the review valence is not evident.

In our context, peer users may share more personal experiences and understanding of common concerns, while group hosts are mainly responsible for providing consulting services and organizing group affairs on behalf of the firm. Based on our data observations, the disclosure from peer users is almost nine times higher (41.7%) than the disclosure from group hosts alone (4.9%), suggesting that group hosts rarely share their personal information in the OCGs. The reasons for this are intuitively understandable as the key duty of brand managers is to provide professional consultancy to customers' queries and some managers may not even have parenting experience. As such, they are less likely to express self-related information.

Next, we run the regression models by dividing the disclosure from other OCG members into peer users and group hosts to evaluate their separate effects on focal users' subsequent engagement. Table 8 reports the results. All the coefficients of peer users' disclosure and their interactions with focal users' disclosure are positive. Surprisingly, while group hosts' disclosure is effective in driving longer messages from customers, we find no significant relationship between group hosts' disclosure and engagement positivity, and the relationship to promptness is even slightly negative. Moreover, the coefficient of the interaction term between group hosts' and focal users' disclosure is significantly negative on engagement positivity (Column (5): Coef. = -0.015). This finding supports previous research (e.g., Wang & Chaudhry 2018) that managers' responses may even backfire the positive effect of focal users' self-disclosure and induce more negative messages in the future. In the presence of overwhelming disclosures from a group of customers, brand managers' personal sharing is almost negligible in the OCGs. Therefore, the effect of brand managers' disclosure is limited, and their interference with customers' discussion may even damage customers' perception of their professionality and demotivate customers from chatting with peers.

Table 8. Results of Disclosures from Peer Users vs. Group Host

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Promptness	Positivity	Effort	Promptness	Positivity	Effort

ODPeer	0.128***	0.029***	1.419***	0.126***	0.026***	1.312***
	(0.025)	(0.005)	(0.324)	(0.025)	(0.005)	(0.331)
ODHost	-0.028	0.004	0.682**	-0.023	0.000	0.650*
	(0.027)	(0.006)	(0.347)	(0.027)	(0.006)	(0.351)
SD	0.057**	0.022***	1.262***	0.055**	0.019***	1.173***
	(0.023)	(0.005)	(0.306)	(0.024)	(0.005)	(0.310)
SD×ODPeer				0.005	0.018***	0.534*
				(0.024)	(0.005)	(0.313)
SD×ODHost				-0.027	-0.015***	-0.097
				(0.022)	(0.005)	(0.284)
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
_cons	-8.328***	-0.173	-43.793***	-8.330***	-0.160	-43.522***
	(0.510)	(0.105)	(6.611)	(0.510)	(0.105)	(6.613)
N	90090	90090	90090	90090	90090	90090
Adjusted R^2	0.151	0.030	0.169	0.151	0.030	0.168

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6.3. (C) Robustness Checks

We also conduct a number of robustness checks: 1) classifying disclosure messages by a Machine Learning (ML) model and re-evaluating the relationships; 2) using alternative matching and sample; 3) separating the effects of disclosure and user activeness; 4) examining alternative measures of user engagement.

6.3.1. Self-Disclosure Predicted by Machine Learning Model.

We refer to the method of Melumad and Meyer (2020) to identify disclosure messages. In addition to the linguistic measures based on LIWC dictionaries, we train a ML model to classify whether a message is relevant to self-disclosure. To implement, we randomly extract 5000 messages from the entire message pool, and recruit 10 undergraduate students to rate the messages using the first four survey items of self-disclosure in Melumad and Meyer (2020, p.34). We then label the message to be a disclosure message if the average response of survey items is larger than four (the neutral point of a 7-point scale). Using this labeled set, we train an attention-based LSTM model for disclosure detection (Hochreiter & Schmidhuber 1997; Vaswani et al., 2017).[14] Considering that the communication style may differ between customers and brand managers, we differentiate these two message sources in the model setup. The final model achieves a good predictive performance.[15] We then apply the model to predict the rest messages in our sample as disclosure messages or not. We re-calculate disclosure variables and run the regressions in the same way as the main analyses. Descriptive statistics show that the average degree of other members' disclosure declines from 41.8% to 26.4% and focal users' disclosure decreases from 57.3% to 36.4%. Nevertheless, the regression results in Table 9 and 10 are generally consistent with the main results, supporting the robustness of our findings.

Table 9. Results of ML-Predicted SD: Overall

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
OD	0.234***	0.044***	1.358***	0.224***	0.039***	1.176***
	(0.024)	(0.005)	(0.314)	(0.024)	(0.005)	(0.316)
SD	0.042*	0.025***	0.322	0.045*	0.026***	0.382
	(0.024)	(0.005)	(0.306)	(0.024)	(0.005)	(0.306)
SD×OD				0.081***	0.040***	1.684***
				(0.021)	(0.004)	(0.267)
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included

[14] Each message was tokenized by a pre-trained BERT model (Cui et al. 2020; Devlin et al. 2018) and was encoded into word vectors to be used in the input layer.

[15] We partition the dataset into training and test sets with 80/20 ratio. The final model has an AUC of 0.931 and a recall of 0.683 in the test set.

Control Variables	Included	Included	Included	Included	Included	Included
_cons	-4.982***	-0.174*	-45.153***	-4.974***	-0.170	-44.466***
	(0.511)	(0.106)	(6.635)	(0.511)	(0.106)	(6.631)
N	90090	90090	90090	90090	90090	90090
Adjusted R^2	0.325	0.032	0.170	0.329	0.042	0.176

Table 10. Results of ML-Predicted SD: Content Intimacy

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
Disclosure Interaction with Consistent Content Intimacy						
CogSD×CogOD	0.005	0.023***	0.981***	0.007	0.031***	1.200***
	(0.017)	(0.004)	(0.239)	(0.018)	(0.004)	(0.258)
PosEmoSD×PosEmoOD	0.028*	0.055***	1.878***	0.046***	0.073***	2.369***
	(0.015)	(0.003)	(0.196)	(0.015)	(0.003)	(0.206)
NegEmoSD×NegEmoOD	0.033**	0.007*	0.356	0.032*	0.012***	0.515*
	(0.016)	(0.004)	(0.223)	(0.019)	(0.004)	(0.264)
Disclosure Interaction with Inconsistent Content Intimacy						
CogSD×PosEmoOD				0.030	0.015***	0.581*
				(0.023)	(0.005)	(0.318)
CogSD×NegEmoOD				-0.073***	-0.048***	-1.740***
				(0.023)	(0.005)	(0.317)
PosEmoSD×CogOD				-0.046**	-0.037***	-1.298***
				(0.020)	(0.005)	(0.282)
PosEmoSD×NegEmoOD				-0.027	-0.046***	-0.628**
				(0.023)	(0.005)	(0.317)
NegEmoSD×CogOD				0.046*	0.009*	0.112
				(0.024)	(0.005)	(0.331)
NegEmoSD×PosEmoOD				-0.023	-0.037***	-1.097***
				(0.030)	(0.006)	(0.375)
Main Effects	Included	Included	Included	Included	Included	Included
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
N	90090	90090	90090	90090	90090	90090
Adjusted R^2	0.419	0.099	0.193	0.421	0.106	0.194

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6.3.2. Alternative Matching.

We also apply the Coarsened Exact Matching (CEM) approach to match users with non-zero self-disclosure and those with zero self-disclosure using the same variables as PSM. After matching, we observe a decrease in multivariable imbalance statistics (L1 distance) from 0.60 to 0.55. Additionally, the univariate comparison of L1 distance indicates that the balance of every covariate is improved after matching. Using the matched sample, we re-estimate the models in Study 1 and Study 2 and report the results in Table 11 and Table 12. The results align with the main findings, providing further support for their robustness.

Table 11. Results of CEM: Overall

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
OD	0.016***	0.030***	1.429***	0.016***	0.027***	1.348***
	(0.003)	(0.005)	(0.331)	(0.003)	(0.005)	(0.338)
SD	0.010***	0.021***	1.315***	0.009***	0.018***	1.786***

	(0.003)	(0.005)	(0.309)	(0.003)	(0.005)	(0.314)
SD×OD				0.005*	0.018***	0.638**
				(0.003)	(0.005)	(0.318)
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
_cons	7.549***	-0.188*	-45.545***	7.551***	-0.180*	23.893***
	(0.071)	(0.107)	(6.835)	(0.071)	(0.107)	(6.291)
N	86452	86452	86452	86452	86452	86452
Adjusted R^2	0.038	0.030	0.168	0.038	0.030	0.169

Table 12. Results of CEM: Content Intimacy

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
Disclosure Interaction with Consistent Content Intimacy						
CogSD×CogOD	0.006**	0.021***	0.506**	0.006**	0.020***	0.650**
	(0.002)	(0.004)	(0.245)	(0.003)	(0.004)	(0.276)
PosEmoSD×PosEmoOD	0.051***	0.051***	1.987***	0.061***	0.082***	2.897***
	(0.002)	(0.004)	(0.231)	(0.002)	(0.004)	(0.241)
NegEmoSD×NegEmoOD	0.007***	0.021***	0.426*	0.010***	0.023***	0.634**
	(0.002)	(0.004)	(0.246)	(0.002)	(0.004)	(0.274)
Disclosure Interaction with Inconsistent Content Intimacy						
CogSD×PosEmoOD				0.005**	0.026***	0.525*
				(0.003)	(0.004)	(0.277)
CogSD×NegEmoOD				-0.030***	-0.050***	-1.851***
				(0.003)	(0.005)	(0.304)
PosEmoSD×CogOD				-0.018***	-0.053***	-1.131***
				(0.003)	(0.005)	(0.309)
PosEmoSD×NegEmoOD				-0.025***	-0.079***	-2.427***
				(0.003)	(0.005)	(0.299)
NegEmoSD×CogOD				0.013***	0.026***	0.557*
				(0.003)	(0.005)	(0.288)
NegEmoSD×PosEmoOD				-0.037***	-0.045***	-1.788***
				(0.003)	(0.005)	(0.308)
Main Effects	Included	Included	Included	Included	Included	Included
User/Group Fixed	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
N	86452	86452	86452	86452	86452	86452
Adjusted R^2	0.314	0.105	0.179	0.322	0.109	0.180

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6.3.3. Separating Disclosure and User Activeness.

It is likely that talkative users may disclose more, and meanwhile, engage more actively in the group. To evaluate this alternative explanation, we hold out each user's first 30 days' data since their first message in our data observational window, and measure their total number of words sent during this period to gauge the propensity of each user's activeness in the OCGs. We remove the fixed effects in the model and run the regressions on the rest of the data window with the user activeness variable. The results in Table 13 show that the coefficients of mutual disclosures remain significant and positive overall. One exception is the interaction of mutual disclosures on engagement effort. The coefficient becomes negative but very marginal (Column (3)). This might be because user activeness suppresses the importance of the complementary effects between mutual disclosures on subsequent engagement effort. Moreover, we explore the interactions between disclosure variables and user activeness. The results show that users who are intrinsically active are less susceptible to others' disclosure. In contrast, the relationships between focal users' self-disclosure and engagement outcomes are further strengthened with a higher level of user activeness. In this sense, users who chat actively in the group may enjoy the process more, which will amplify their reactions to self-disclosure and subsequent engagement.

Table 13. Effects of Mutual Disclosures and User Activeness

Variables	(1) Promptness	(2) Positivity	(3) Effort	(4) Promptness	(5) Positivity	(6) Effort
OD	0.321***	0.041***	0.829*	0.312***	0.036***	0.534
	(0.032)	(0.007)	(0.448)	(0.032)	(0.007)	(0.447)
SD	0.035	0.070***	5.374***	0.039	0.071***	5.638***
	(0.029)	(0.006)	(0.417)	(0.029)	(0.006)	(0.416)
SD×OD	0.210***	0.026***	-0.757*	0.205***	0.024***	-0.933**
	(0.030)	(0.006)	(0.427)	(0.030)	(0.006)	(0.426)
Activeness	2.350***	0.208***	29.136***	2.399***	0.231***	31.147***
	(0.037)	(0.008)	(0.531)	(0.038)	(0.008)	(0.538)
OD×Activeness				-0.280***	-0.151***	-9.694***
				(0.044)	(0.009)	(0.628)
SD×Activeness				0.112**	0.028***	6.386***
				(0.045)	(0.010)	(0.644)
Month Dummies	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included
_cons	-1.454***	0.293***	0.355	-1.445***	0.300***	0.084
	(0.289)	(0.062)	(4.779)	(0.289)	(0.062)	(4.762)
N	60776	60776	60776	60776	60776	60776
Adjusted R^2	0.228	0.037	0.079	0.229	0.049	0.103

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

6.3.4. Alternative Measures of User Engagement.

We further examine the relationships between mutual disclosures and several alternative measures of user engagement. First, in the main analyses, we include those who did not participate in the subsequent week and code their aggregated dependent variables as zero. This allows the coefficients to indicate the overall effects on users' engagement tendency and intensity. Here we exclude the records of the users whose subsequent engagements are missing and focus only on those who continued to engage in OCG discussions in the subsequent week, to estimate the effect of mutual disclosures on their engagement intensity explicitly. The results are reported in Columns (1)-(3) of Table 14. Second, we narrow the time window of subsequent engagement into *three calendar days* and examine the relationships. Results are shown in Columns (4)-(6). Third, we use focal users' total word and message count in the next three days as the dependent variables to replace the ratio-based engagement measures (see Columns (7)-(8)). Overall, the results of these robustness tests suggest consistent patterns with our main findings.

Table 14. Results of Alternative Engagement Measures

DV:	(1) Prompt. (engaged)	(2) Pos. (engaged)	(3) Eff. (engaged)	(4) Prompt. (3-days)	(5) Pos. (3-days)	(6) Eff. (3-days)	(7) # of Word (3-days)	(8) # of Msg (3-days)
OD	0.015***	0.023**	0.942*	0.137***	0.011***	0.540**	0.077***	0.062***
	0.003	0.009	0.561	0.022	(0.003)	(0.211)	(0.006)	(0.006)
SD	0.005*	0.028***	2.963***	0.051**	0.010***	0.716***	0.013**	0.023***
	0.003	0.008	0.511	0.020	(0.003)	(0.198)	(0.006)	(0.006)
SD×OD	0.007**	0.018**	0.226	0.220***	0.008***	0.245	0.064***	0.043***
	0.003	0.009	0.540	0.040	(0.003)	(0.200)	(0.006)	(0.006)
User/Group Fixed	Included	Included	Included	Included	Included	Included	Included	Included
Month Dummies	Included	Included	Included	Included	Included	Included	Included	Included
Control Variables	Included	Included	Included	Included	Included	Included	Included	Included

_cons	7.486***	0.091	81.013***	-3.429***	-0.070	-15.315***	-5.613***	-3.831***
	0.067	0.196	9.797	0.396	(0.067)	(4.213)	(0.057)	(0.060)
N	49251	49251	49251	90090	90090	90090	90090	90090
Adjusted R^2	0.018	0.019	0.007	0.027	0.023	0.106	0.074	0.125

Note: *p<.10; **p < .05; ***p<.01. Standard errors are in parentheses.

7. DISCUSSION AND CONCLUSIONS

This paper examines the role of self-disclosure in online group conversations. Differentiated from public platforms and private live chats, our study is motivated by the unique features of the OCG context and examines how mutual disclosures are related to user engagement in three aspects: promptness, positivity, and effort, based on the disclosure–liking framework (Collins & Miller 1994). Moreover, we investigate the interactions of mutual disclosures regarding content intimacy. The findings demonstrate significant synergy of mutual disclosures among OCG users. We also find multifaceted interactions of mutual disclosures with different combinations of content intimacy. The results are further verified in a controlled experiment and show robustness to alternative disclosure and engagement measures. Moreover, we differentiate the disclosures from peer users and group hosts in OCGs, and demonstrate that user engagement in OCGs can be effectively motivated by peer disclosures; however, the role of group hosts is rather limited and sometimes even demotivates group members' engagement. Our work contributes to the UGC literature by extending the understanding of how self-related information exchange can be leveraged to motivate user engagement in OCGs. We also contribute to the disclosure literature by distinguishing the source of disclosure and exploring the interplay of disclosure depth in OCG conversations. Our results have important theoretical and practical implications.

7.1. Theoretical Contributions

Our study makes contributions to the confluence of literature streams concerning group conversations, UGC, and self-disclosure. First, OCGs have evolved into vital communication channels in daily life. However, there is a dearth of IS research aimed at understanding user behavior within this sphere. In our study, we conceptualize the distinctive characteristics of OCGs and compare them to public platforms, such as social media, and private live chats, such as one-to-one instant messaging tools. We elucidate that OCGs function as semi-private communities that connect groups of users and possess attributes of exclusivity, conversation, interactivity, and anonymity. These attributes foster a more robust sense of community among users compared to public platforms and facilitate intragroup interactions. OCGs can have diverse applications in both personal and professional realms. While our empirical analysis focuses on the application of OCGs for customer service, the research findings are broadly generalizable to other OCGs sharing similar contextual features. However, it is important to note that these findings may not be applicable to OCGs that diverge from these features, such as parent-teacher or colleague groups, where anonymity is not maintained. To the best of our knowledge, we are among the first in examining user engagement in online group conversations within the IS literature. Our study not only supplements existing research on social media and traditional online communities but also charts new avenues for examining individual behavior in the OCG context and encourages further exploration of OCG applications in business.

Second, our study enriches the UGC literature about user engagement from the perspective of self-disclosure. Although recent research has begun aiming at the effect of information content and interactions between users and businesses (e.g., Chen et al. 2019; Ordenes et al. 2019), little research has been devoted to investigating the interplay of self-related information exchange in content generation. Motivated by the OCG features, we fill the research gap by taking into account self-disclosure in OCG conversations and examining its relationships to user engagement. Building on the theoretical framework of disclosure–liking (Collins & Miller 1994), our research investigates disclosures among OCG users with granular analysis, which further reveals the underlying mechanisms of user engagement in online group conversations.

Third, we leverage the self-disclosure theory and differentiate disclosures from opposite sources in user dialogues, which we refer to as mutual disclosures. The disclosures sent to and from focal users are correlated and thus must be evaluated simultaneously to disentangle their influences. Otherwise, their effects will be confounded. Our findings verify the necessity of distinguishing mutual disclosures and show their complementary effects on user engagement in OCGs. Furthermore, we delve into the intimacy levels of disclosure content and explore the interactions of mutual disclosures regarding content intimacy consistency. Our findings demonstrate the nuanced interplay of content intimacy between mutual disclosures. On the one hand, users prefer consistent dialogues to feel understood by other users, so that they would be willing to engage in OCG conversations more actively in the future. On the other hand, not all dialogues with inconsistent content intimacy hinder user engagement. Users' incentive of engagement can be fostered under some inconsistent disclosing circumstances. Our study advances the literature on disclosure by adding the knowledge of disclosure interactions with respect to not only disclosure breadth (amount) but also disclosure depth (content) in the OCG context.

Last but not least, we conceptualize user engagement in three aspects in the OCG context: promptness, positivity, and effort. Higher values of these variables denote that users send messages with shorter periods, more positive expressions, and longer sentences. These outcomes characterize user engagement beyond engaging volume and valence, which are mainly adopted in the previous UGC literature. Instead, they imply users' emotional and cognitive commitment to the OCGs, and moreover, quantify their engagement behavior from the time dimension to capture the unique time-sensitive nature of chat mode in the OCG context. Our dependent variables represent user engagement over a period of time and reveal the effect of self-disclosure on relatively stable consequences.

7.2. Practical Implications

Our paper delves into a pivotal business strategy that leverages online group conversations to engage users. OCGs are founded on social networking tools and generally incur minimal costs while offering managers an efficient means to intimately interact with groups of users through real-time conversations. As such, they present an avenue for firms to conveniently connect with their customers by utilizing this social channel. Moreover, OCGs empower firms to tailor their services for specific customer segments within a relatively private and controlled communication environment. Our research examines the strategic utilization of OCGs to deliver customer services through engagements in online group conversations.

In particularly, our findings underscore the importance of encouraging self-related information exchange, especially mutual disclosures among customers themselves, in firms' strategy designs for fostering customer relationships. We emphasize the role of "mutual disclosures" in conversations. The essential idea of our research is that being "open" about self and "empathetic" to others are significant for engaging recipients (i.e., customers). As noted in Wright (2000), peer-to-peer discussion with similar users could encourage mutual empathy and help people reduce their feelings of isolation, which cannot be achieved by consulting professionals or experts. Our findings in additional analyses confirm that disclosure from peer customers shows strong main and interaction effects on focal customers' engagement. However, the effect of brand managers' disclosure is limited in our example. The results show that disclosure from brand managers can motivate longer messages from customers, but it can increase neither the promptness of their responses nor the positivity of customers' messages. Echoing the findings from previous UGC literature (e.g., Ma et al. 2015), brand managers' disclosure may even hurt customer engagement in terms of positivity, such as eliciting more complaints in the future. Therefore, in comparison to brand managers' intervention in OCGs, peer users/customers should be the focus as they generate empathy and stimulate discussions with each other. This observation sheds light on why in numerous OCGs, where group hosts predominantly disseminate advertisements, notifications, or news, the responses from group members tend to be passive, leading to relatively subdued activity within the groups. In contrast, groups where members actively engage in discussions, share personal experiences, insights, and emotions with each other, tend to sustain lively user engagement over an extended period.

Our findings suggest that if firms aim to forge strong bonds with customers and maintain an active customer community, merely training brand managers to act as professionals is not an effective strategy. This is because, in doing so, brand managers might lose their capacity to empathize as customers. Instead, it is advantageous for brand managers to take on the role of peer users, incorporating more first-person pronouns, personal topics, and occasionally even expressions of negative emotions in their communications with customers. This approach is likely to elicit greater self-disclosure from customers. Simultaneously, brand managers should empathize with customers by putting themselves in the customers' shoes, understanding their concerns, and offering self-disclosure with content that is aligned in terms of intimacy, such as providing emotional support. Mutual disclosures can exponentially enhance customer engagement in group communications. Consequently, firms may witness an increase in customers' affinity for the service groups, which in turn can boost customer satisfaction and brand loyalty. In particular scenarios, such as when the intimacy of content shared by customers is inconsistent, potentially diminishing their subsequent engagement, brand managers need to intervene and steer the discussions towards a more balanced footing. Cognitive disclosure proves beneficial, especially when faced with negative sharing or discussions, as it promotes continued engagement. Our research findings offer actionable insights to bolster user engagement in OCG conversations and illustrate the critical role of disclosure interactions in customer service communications, generating insights for conversational commerce.

7.3. Limitations and Future Research

Our study also has several limitations that warrant exploration in future research. First, the majority of the users in our study are likely to be female (predominantly mothers). Past studies have reported that females tend to disclose more than males (Jourard & Lasakow, 1958), and the relationship between disclosure and liking is stronger among females (Derlega & Chaikin, 1976; Kleinke & Kahn, 1980). While existing research supports the importance of understanding disclosure in our context, this also suggests that our findings should be interpreted with caution and may not necessarily be generalizable to contexts where males predominate. Although we incorporated individual fixed effects to control for user heterogeneity in our models, ideally, a gender variable should be included to directly assess its effect. Furthermore, the conversations in our empirical study primarily revolve around topics related to maternal and childcare. We did not extensively investigate the subjects of the conversations or their outcomes in the present study. Future research could evaluate the success of conversations, such as problem-solving and consensus-building, in relation to various conversational objectives.

Second, in an effort to understand the effect of disclosure depth, we concentrate on the interplay between mutual disclosures and the consistency of content intimacy within them. Consequently, we gauge the content of disclosures from each participant separately and scrutinize their interactions in relation to focal user engagement. This approach allows us to observe how the effect of focal users' disclosures varies in conjunction with different content disclosures from others. However, future research could delve into the effect of intimacy consistency more directly by quantifying the degree of similarity between disclosure contents.

Third, although we address the valence of emotional disclosure in two dimensions - positive and negative - we do not delineate the intensity of various emotions in terms of arousal or activation levels. Prior research has emphasized the significance of emotional arousal in shaping perceptions of reviews (Yin et al., 2017). Berger and Milkman (2012) found that news articles evoking high-arousal emotions, such as excitement and anger, are more likely to be discussed compared to articles eliciting low-arousal emotions, like sadness. Future research, therefore, could investigate how varying intensities of emotional disclosure influence the extent of discussions in OCGs.

Fourth, the current research is designed to understand the effect of disclosure on subsequent user engagement in OCGs, using content generation in the subsequent period (week) as the dependent variable. While we incorporate past engagement in the models to account for historical influences, we do not explicitly model the dynamic process of disclosure, whereby earlier disclosures may prompt further disclosure and the intimacy level of the disclosure may evolve over time (Miller et al., 1983; Morton, 1978). In our study, we make the assumption that the effect of mutual disclosures on user engagement remains constant over time. An interesting extension could be to employ a dynamic panel model to capture the progression of disclosure changes. Additionally, we consider disclosures from other members in conversations as a homogenous entity. Future research could examine the effects of dyadic disclosure between OCG users, taking into account their awareness of the presence of others.

Finally, in this study, we concentrate on customer service management and scrutinize the outcomes of content generation and user perceptions, such as liking. Due to the constraint of identity anonymity in OCGs, we are unable to ascertain users' real identities or obtain marketing data such as purchase decisions. According to Yin et al. (2021), negative emotional expressions, though potentially less helpful, can be more persuasive in influencing customers' attitudes and decisions. It would be valuable to expand the examination of the effects of mutual disclosures to encompass consumer behaviors and investigate the economic value of OCG communications in future research.

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APPENDIX A1: CONVERSATION EXAMPLES IN THE EXPERIMENT

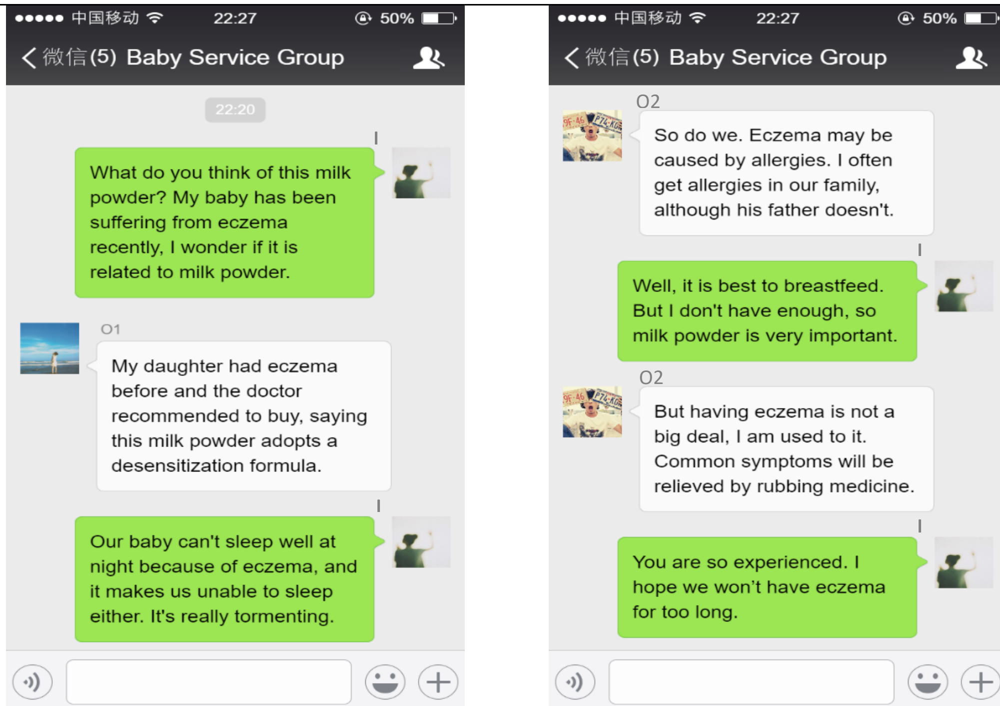

Figure A1. Conversation in the high SD and high RD condition

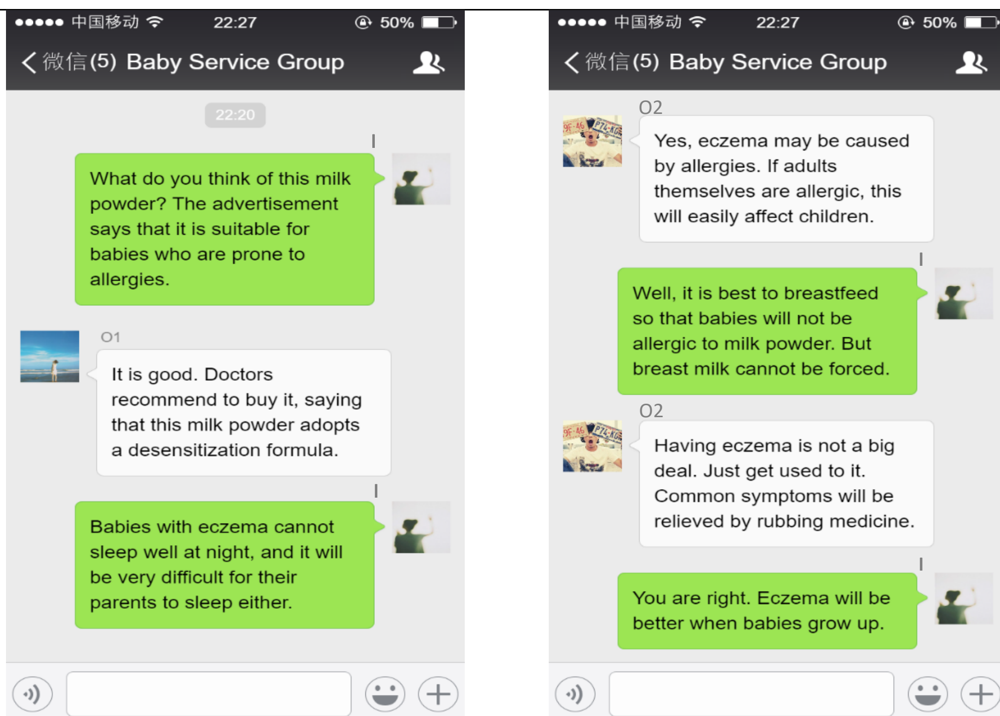

Figure A2. Conversation in the low SD and low RD condition

Note: Due to page limits, we omit the “low SD × high OD” and “high SD × low OD” scenarios. The content is similar to the above scenarios but rearranged for different combinations of high/low conditions.

APPENDIX A2: MEASUREMENTS IN THE EXPERIMENT

Imagine that you are the person **"I"**, and persons **"O1&O2"** are other members in this online chat group (OCG)**.** After you read the conversation, please answer the following questions regarding your attitudes toward this OCG.

(1=strongly disagree; 2=moderately disagree; 3=somewhat disagree; 4=neutral; 5= somewhat agree; 6= moderately agree; 7= strongly agree)

Liking (adapted from Rubin's liking scale: Rubin 1973; Collins and Miller 1994)

1. I like this online chat group.
2. I like sharing my opinions and feelings in this chat group.
3. The other OCG members are very likable people.
4. I think that other OCG members and I are quite close to each other.

Engagement Positivity

5. I am willing to share positive feelings in this OCG.
6. I will send messages positively in this OCG.

Engagement Effort

7. I am willing to chat seriously in this OCG.
8. I will make an effort to chat in this OCG.

For manipulation checks (Melumad and Meyer 2020)

(1=not at all; 2=minimal; 3=mild; 4=moderate; 5=somewhat a lot; 6=quite a lot; 7=very much)

Focal Users' Self-Disclosure (SD)

1. To what extent does the person **"I"** reveal personal feeling, thoughts, or opinions in this conversation?
2. To what extent does the person **"I"** disclose personal information about him/herself in this conversation?

Other Members' Disclosure (OD)

3. To what extent do the persons **"O1&O2"** reveal personal feeling, thoughts, or opinions in this conversation?
4. To what extent do the persons **"O1&O2"** disclose personal information about themselves in this conversation?

What is your gender? Male/Female

Do you have parenting experience? Yes/No