Impact of Content Ideology on Social Media Opinion Polarization: The Moderating Role of Functional Affordances and Symbolic Expressions

Abstract. We offer theory and evidence regarding the impact of content ideology (i.e., emotionally charged beliefs expressed in sentiments) on opinion polarization (i.e., conflicting attitudes about an event) on social media. Specifically, we consider the moderating role of functional affordances and symbolic expressions to draw inferences about opinion polarization. From a sentiment analysis of 3,600 posts and a survey of 468 Weibo users, we find that content ideology is positively related to social media opinion polarization. The effect of content ideology is greater when users receive stronger symbolic expressions. Further, our results show an insignificant moderating relationship between functional affordances and this effect. The findings suggest that it is critical to consider content ideology and symbolic expressions when assessing the relationship between published content and polarized opinions on social media.

Keywords: social media, opinion polarization, sentiment analysis, ideology, functional affordance, symbolic expression

1. Introduction

Opinion polarization describes the phenomenon of people holding contrasting attitudes towards an event [1]. For example, Donald Trump’s posts often raised heated debates and led to personal abuse on Twitter. Opinion polarization is pervasive in political discourses, where people’s contrasting viewpoints further separate different partisans [2]. Because social media (e.g., Twitter, Facebook, and Weibo) allows people to easily access information and express opinions in public with lower cost and fewer consequences, opinion polarization has been expanding from political discourses to broader topics, ranging from social events to celebrity behaviors and sport competitions [3–5]. Consequently, opinion polarization on social media has been designated as a major digital and social risk by the World Economic Forum [6].

Despite decades of research endeavors, there is a lack of understanding on how to control social media opinion polarization. To examine such polarization, a growing body of literature has focused on the role of *echo chambers*, which describes a situation in which people are prevented from being exposed to information that contradicts their existing beliefs [7,8]. That is, when people use social media, exposure to information is mediated by computing algorithms according to users' online behaviors. For example, Facebook employs users' online behavior data (e.g., profile details, engagement patterns, and web browsing history) to ensure the news feed shows users the posts they would like to see [9]. In this case, algorithmic sorting induces users to deliberately select favored information to read and likeminded accounts to follow, thereby separating people with contrasting opinions [10,11].

Although echo chambers reinforce opinion polarization on social media, such reasoning is conditional on the assumption that social media users exist in echo chambers before opinion polarization occurs [12,13]. However, we argue (and provide empirical evidence) that this assumption is only true if social media effectively exposes algorithmically sorted content to users. Specifically, we posit that one important cause of social media opinion polarization is how content is *presented* and *communicated* (not only algorithmically sorted) to users, which influences their decision to agree or disagree with this content.

Our conjecture is in line with the literature that embraces a sentiment perspective on social media opinion polarization [12,14]. In general, the literature indicates an interaction between sentiment exposure to social media users and opinion polarization formation [14]. That is, opinion polarization is more likely to occur when people receive strong reinforcing signals from what their online network posts [13]. Because sentiment content can directly reflect people's psychological states and ideological preferences [15], a direct causal factor of opinion polarization can be the emotionally charged beliefs of the content, which we refer to as *content ideology*. Although the sentiment perspective offers a useful base to study content ideology and social media opinion polarization, empirical examination is still inadequate.

Content ideology is independent of algorithmically generated echo chambers and sources of sentiment content because people with polarized opinions are not necessarily exposed to content under similar ideological preferences, or the polarized opinions are not shared by the same clusters of online networks [13,16]. For example, many social media users deliberately seek attitude-challenging content because they can present a unique self-identity by expressing conflicting opinions [10,17]. This phenomenon challenges the longstanding findings about the dominating role of echo chambers and calls for research attention beyond the sources of content in creating social media opinion polarization [4]. Thus, we aim to understand such polarization by empirically exploring and examining the potential causal effects of content ideology and how social media may transform such effects.

The effect of content ideology on opinion polarization in a social media context deserves more research attention. For example, a study found that in tweets about the legality of cryptocurrencies, strong ideological preferences embedded in the tweets are an important signal that attracts users with different opinions and causes disputes on Twitter [18]. However, few studies have explored whether and how content ideology affects the formation of polarized opinions on social media. Further, although the effect of content ideology may be expected, the literature underscores the importance of technology-enabled contextual factors that may moderate the effect, such as *functional affordances* (action possibilities between technology and a person) and *symbolic expressions* (communicative possibilities between technology and a person) [19]. Social media has similar functional offerings (e.g., @, #, and URL) to enable content diffusion and similar communicative symbols (e.g., numbers of likes, comments, and shares) to communicate content popularity [20,21]. However, how functional affordances and symbolic expressions interact with content ideology and affect opinion polarization is underexplored. Thus, we seek to answer two research questions:

(1) How does content ideology affect opinion polarization on social media?

(2) How do social media functional affordances and symbolic expressions moderate the effect of content ideology on opinion polarization?

We used a survey approach to answer the research questions. Based on 468 Weibo users' responses, our findings demonstrate that the effect of content ideology on social media opinion polarization varies by symbolic expressions. In general, we find that posts with more aggressive and constructive content are associated with stronger opinion polarization. Further, the findings demonstrate variation in opinion polarization with different levels of symbolic expressions. Specifically, we find a positive moderating relationship between symbolic expressions and the effect of content ideology on opinion polarization. However, departing from the literature, we find an insignificant moderating effect of functional affordances on opinion polarization formation.

Overall, our study makes important contributions by providing an alternative view to understand opinion polarization on social media over algorithm-based, echo chamber assumptions [12,13]. Specifically, our findings highlight that opinion polarization is contingent on how social media content is ideologically presented and communicated to users. We extend the literature with a sentiment perspective on opinion polarization into topics broader than political discourses and into an affordance regime by confirming that symbolic expressions can strengthen the effect of content ideology on social media opinion polarization [19,22]. Further, our study is highly relevant for multiple practitioners. Our findings can enable regulatory bodies to detect potential cyberviolence with content ideology as an important indicator. Our findings also imply that social media designers should control symbolic expressions to avoid the spreading of content with strong vicious ideology.

2. Conceptual Background

2.1. Social Media Opinion Polarization

Opinion polarization describes the phenomenon in which a social group is divided into two opposing subgroups with conflicting attitudes towards an event [1]. Scholars identify opinion polarization as a major concern because it can lead to extremism and social chaos [23,24]. The literature identifies social comparison and selective exposure as two main causes of opinion polarization in an offline context [25,26]. Social comparison may stimulate opinion polarization because people's desire to avoid being labelled as deviant drives the reinforcement of existing opinions to refuse opposite voices [27]. Selective exposure is the tendency to selectively favor a person's existing opinion, thereby accumulating supportive evidence but ignoring disagreements [28].

When examining opinion polarization in an online context, the literature generally argues that social media induces more polarized attitudes as a result of echo chambers [3,29]. For example, Lawrence et al. [30] conducted an online survey about social media users' attitudes towards political factions and found that left-wing and right-wing users were mindfully further apart because they would only read filtered articles that were in line with their political attitudes. Social media can exacerbate the tendency of users to select content that reinforces their existing preferences through algorithmic filters based on their browsing history and personal profiles [9]. In this case, social media's networking and categorizing algorithms expose people to an echo chamber [31]. In an echo chamber, social media users seek likeminded opinions but avoid dissimilar viewpoints, which leads them towards more extreme opinions [16,32].

Despite the examined effect of echo chambers on social media opinion polarization, we argue that there is a potential risk. That is, the echo chamber perspective assumes that social media users exist in algorithmically created echo chambers before opinion polarization occurs [9,29,30]. However, Shore et al. [12] found evidence of opinion polarization but no evidence of echo chambers on Twitter. Indeed, social media provides unprecedented opportunities for free public expression and diverse methods of information dissemination. For example, Conover et al. [2] found that Twitter users “retweet” likeminded others but “@” users they disagree with to strengthen their opinions. Many social media users are aware of content with contrasting opinions and may even interact with people who have contrasting opinions [13]. Thus, we posit that an underrated aspect of social media opinion polarization is how social media presents and communicates (not only sorts) content to users.

The sentiment perspective provides an appropriate base to examine our hypothesis [12,33,34]. In general, the sentiment perspective argues that social media opinion polarization is likely to occur when people receive strong reinforcing signals from what their online network posts [13]. That is, people tend to articulate what they perceive to be mainstream based on the predominant sentiments from their information source, rather than only reply on the information source itself [14]. In this case, opinion polarization relates to how people interact with content on social media. As Kitchens et al. [14] suggested, “social, attitudinal, and affective polarization are all potential antecedents or consequences of the content a user is exposed to, engages with, and consumes.”

Although the sentiment perspective offers a useful theoretical basis for examining social media opinion polarization [12,14], no investigations have empirically revealed how social media content (e.g. posts) may induce opinion polarization. Table 1 summarizes our review of empirical literature on opinion polarization and shows that we need a more in-depth understanding of what characterizes content on social media. Further, the empirical evidence is restricted to organizational and community settings in earlier stages [25,35,36]. Although some studies have examined opinion polarization of political discourses on social media [12,14,34], our understanding of opinion polarization under other popular topics, such as entertainment, current affairs, and social events, remains limited. To set a strong conceptual foundation for our empirical work, we further interpret the concepts of content ideology, functional affordances, and symbolic expressions as important characteristics that complement the sentiment perspective on social media opinion polarization.

Table 1 Summary of Empirical Literature on Opinion Polarisation

Context	Antecedent	Effect	Key finding	Source
Group decision making in organizations (communities)	Communication cues and anonymity	Group polarization	Removal of visual cues and anonymity can reduce social presence to raise group polarization.	[25]
	Computer-mediated communication	Group polarization	With decision support systems, group polarization occurs to significantly lesser degree than face to face (F2F) situations.	[35]
	Computer-mediated communication	Group polarization	Group member decision preferences under computer-mediated communication is more polarized than under F2F communication.	[36]
	Quantity and conformity of group argument	Polarized attitude towards rumours	With the continuous increase in quantity and conformity of group arguments, users' attitudes toward rumours are polarised.	[37]
Political discourses on social media	Sources of politic slant	Social media polarization	Members of a small network core exhibit cross-sectional evidence of polarisation.	[12]
	Individual social media use	Degree of polarization shift	Facebook use is associated with a shift toward more polarized sources. Effects of Reddit and Twitter uses are moderate and non-sufficient.	[14]
	Toxicity of online content	Political polarization	The toxicity in COVID discussions can fuel political polarization and leads to prominent positions in ties of COVID news sources on Reddit.	[34]

2.2. Content Ideology

Ideology as a concept was initially established by Destutt de Tracy in 1801 [38] to describe a science of ideas that systematically seeks the truth. Marx and Engels then referred to the concept of ideology as people's beliefs to justify their domination and the status quo to consolidate their existing social and political stands [39]. More recently, scholars have used ideology to describe shared, relatively coherently interrelated sets of emotionally charged beliefs, values, and norms that bind some people together and help them make sense of their world [40,41].

A useful concept for communicating ideology is *linguistic ideology*. Silverstein [42] defines linguistic ideology as "sets of beliefs about language articulated by the users as a rationalization or justification of perceived language structure and use." Specifically, linguistics is a vehicle for semantic varieties that reflect a person's demographics, psychological states, and ideological preferences [43]. For example, in 2013, Quebec police sent a letter of warning to an Italian restaurant owner objecting to the use of Italian words "pasta" and "bottiglia" on the menu because the Language Office considered these Italian words linguistic offenses that threatened local culture [44].

Thus, the focus of this study is written discourses (e.g., blog narrations and post sentiments) on social media. This focus reflects the prominence of textual presentation as a basis for expressing ideology on social media [43,45]. For example, internet users rely on their stereotypes of online content's level of aggressiveness (constructiveness) to interpret a publisher's feelings, beliefs, and intentions and, in turn, to decide how to react to the publisher [46]. In a related context, some literature has examined the effect of language aggressiveness on the persuasiveness of social media content [47,48]. For example, Li and Du [49] found that opinion leaders on microblogging platforms are more aggressive in distributing positive messages than those who distribute negative messages. Thus, one inherent implication of the literature is that written discourses, as the linguistic representation of ideology, can affect users' cognition on social media.

Drawing on the above discussion, we use the term *content ideology* to describe written discourses that represent a person's ideological beliefs, and we explore its causal effect on social media opinion polarization.

2.3. Functional Affordances and Symbolic Expressions

Our basic assumption relates to content ideology because how people react to the content must relate, at least in part, to how the content is discoursed. Content ideology is naturally embedded in these discourses. However, if this assumption stands, how is social media different to traditional media (e.g., newspapers)? To provide a plausible basis for our assumption, we need a conceptual foundation that describes the specificity of social media. A useful conceptual lens is the affordance view [19,50].

Gibson [51] first introduced the concept of "affordances" to describe action possibilities emerging from objects in ecological psychology. For example, a bench affords a person the possible action of sitting. Affordances are a type of relationship between objects and people. The same object (e.g., a bench) may embrace different affordances (e.g., sitting, lying, and standing) depending on how people perceive them (e.g., to rest, to sleep, and to see further). Thus, affordances naturally exist with objects and need to be perceived [52]. Information systems (IS) scholars have extended the concept of affordances to theorize action possibilities between technology objects (e.g., system features) and actors (e.g. system users) and labelled it *functional affordances* [19,20]. Further, IS scholars have used the affordance view to examine a range of social media phenomena, including the use of social media and connective actions [20], social media features and knowledge sharing [53], and motivation for social media use [21].

Although we have discussed a system's action possibility, a relevant but often overlooked aspect is how the meaning of a system's action possibility is communicated to users. Symbols serve as a means to communicate information [54]. A technical object is designed with symbols to express the intended meaning of use [22]. For example, the symbol "🖂" is associated with the meaning "create an e-mail" in Microsoft Outlook. IS scholars use the term *symbolic expressions* to describe "the communicative possibilities of a technical object for a specified user group" [19] and to encompass "how users interpret and react to an IT artefact" [55]. Like functional affordances, symbolic expressions describe a relationship between objects and people. Symbolic expressions are inherently associated with people's representations of experiences that guide perception and action [22]. Thus, symbolic expressions represent a kind of "heuristic that helps people process incoming information" [55].

To summarize, although functional affordances and symbolic expressions are important for understanding how content arises and is communicated between a technology object (here, social media) and users, their roles in relation to social media opinion polarization remain unclear.

3. Hypothesis Development

Building upon the conceptual background, we elaborate on the hypotheses for empirical testing in this section. Figure 1 depicts the hypotheses.

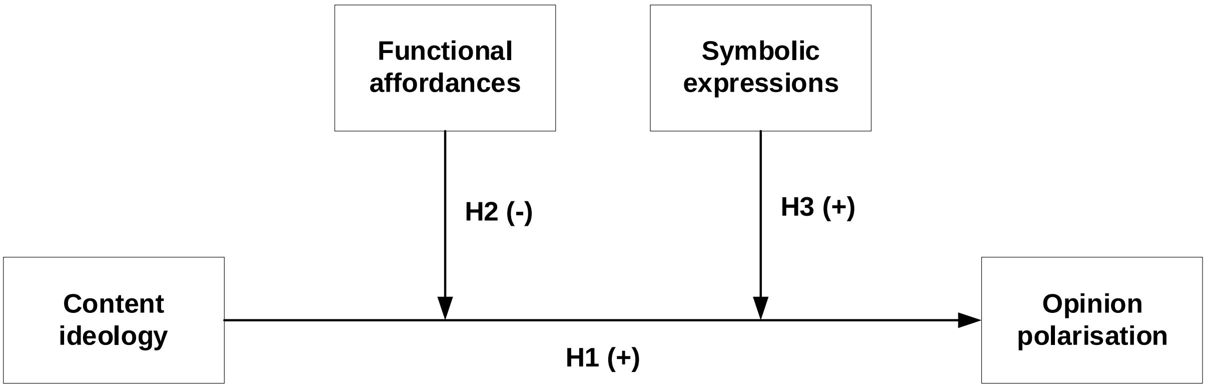

Figure 1. Research Model

3.1. The Effect of Content Ideology on Opinion Polarization

In our study, content ideology describes the emotionally charged representation of sentiments in social media posts. Users select what they read on social media because it is impossible to read all social media content. To attract readership, social media content is often embedded with strong content ideology [49,56]. Chipidza et al. [34] showed that toxic content (i.e., the use of rude, disrespectful, or unreasonable language in Reddit posts) was more likely to be shared among social media users, which could denigrate ideological opponents. Thus, opinion polarization may be sharpened with such toxic content. For example, tweets with more aggressive content (e.g., "F**k Trump") are more likely to result in greater disagreement between Trump's supporters and opponents than tweets with gentler content (e.g., "I disagree with Trump"). Similarly, Calais Guerra et al. [57] found that the intensity of polarized debates on gun control increased when posts showed more "opinionated content" on Twitter. Further, linguistic resources have been used in sentiment polarity determination [33]. As Shore et al. [13] suggested, "polarized [Twitter] users are rare," and if we want to study polarization on social media, we are "better off looking at what they [social media users] read than at what they say." However, many content creators deliberately use extremely aggressive or constructive language to increase social media engagement [56], which may separate people with different opinions [12]. In this case, we expect that opinion polarization can be derived from the ideological sentiment embedded in a post, especially when the post is framed with rhetorical content to be persuasive or impressive [58]. Thus, we hypothesize:

Hypothesis 1 (H1): For a social media post, more extreme content ideology leads to stronger opinion polarization.

3.2. The Moderating Effect of Functional Affordances

Functional affordances are rooted in the action potential offered by a technology [19]. Social media functional affordances offer the key action possibility of disseminating user-generated content [21,53]. On social media, one can easily and widely spread ideas by posting short messages and making the messages accessible to the public [53]. Because one can choose to use different features offered by social media platforms, some posts embrace more functional affordances (e.g., using @, #, and URL) than others (e.g., using text only) [59]. Content with fewer affordances suggests approximate and insufficient information [60]. First, the literature suggests a sequential interdependence of social media affordances [20]. That is, content generation often precedes the use of other affordances (e.g., @, #, and URL). In this case, social media affordances reshape the relationship between the content and content reading [59].

Specifically, affordances can facilitate the codification and sharing of complex information on social media [61] and thus make users pay more attention to the overall meaning of extreme content ideology rather than its parts, which may alleviate the positive effect of content ideology on opinion polarization. Second, the cognitive authority theory suggests that accuracy, reliability, comprehensiveness, and validity determine people's judgement of online information quality [62]. When information is approximate and insufficient, the effect of content ideology on opinion polarization may increase because contextual information about the focal event is less exposed to readers. In this case, readers are more likely to be cognitively polarized as a result of self-knowledge and one-sided opinions [63]. For example, Boot et al. [64] showed that Twitter's extension of character limit (stronger affordances for information capacity) reduces the likelihood of judgements being made based on self-knowledge. In this case, posts with richer functional affordances should embrace higher information quality and decrease the effect of extreme content ideology. Thus, we expect that increasing functional affordances weakens the relationship between content ideology and opinion polarization. Based on the preceding discussion, we hypothesize:

Hypothesis 2 (H2): For a social media post, functional affordances negatively moderate the effect of content ideology on opinion polarization.

3.3. The Moderating Effect of Symbolic Expressions

Symbolic expressions communicate the meanings made possible by a technology's action potentialities [22]. Given that symbols (e.g., "👍") invite their own meanings (e.g., agreement) on social media, we should consider whether particular symbols are congruent with users' cognitive schemas and how they may affect the relationship between content ideology and opinion polarization. Specifically, the literature suggests that people strive for consistency between cognitive schemas (i.e., values, feelings, behaviors, and experiences) [65]. Cognitive schemas "represent a kind of heuristic that helps people process incoming information" [55]. For example, consider two tweets (A and B) that describe the same event with the same content ideology (e.g., using extreme aggressive terms to support Trump). Tweet A shows "12.6K shares, 9,730 comments, and 42.6K likes," whereas B shows "2 shares, 1 comment, and 3 likes". Tweet A signals that it is more influential than B. People's basic psychological needs to influence the environment and express their self-identity motivate users to pay more attention to A than B [66]. In this case, A is likely to result in stronger opinion polarization than B because users will highlight their self-identity by comparing their cognitive schema with more influential content [67]. Further, symbolic expressions are "socially constructed by a specific group of users, and thus must be understood dependent on the social context" [68]. In this case, content with a similar ideology but stronger symbolic expressions may further separate different groups of people with different social stands (e.g., people who support and oppose Trump). Thus, we expect that stronger symbolic expressions suggest a positive moderating effect between content ideology and opinion polarization. Specifically, we hypothesize:

Hypothesis 3 (H3): For a social media post, symbolic expressions positively moderate the effect of content ideology on opinion polarization.

4. Research Method

4.1. Research Context and Empirical Setup

To achieve our research aim, we constructed our dataset by retrieving trending topics on Weibo in 2020. We selected Weibo as our data source because around 50% of social media users are from China[1]. Further, we used Weibo's "Hot Search"[2] (similar to "trending" on Twitter) to identify events that had attracted widespread public attention because they indicated a higher likelihood of accommodating the variables to be

[1] See Statista: https://www.statista.com/statistics/278341/number-of-social-network-users-in-selected-countries/
[2] Hot Search provides real-time ranking of the most popular 50 topics based on the number of searches and engagements.

examined. Finally, we decided to focus on topics in 2020, given the dramatic increase in the number of social media users because of the quarantine and work-from-home policies resulting from COVID-19[3]. We observed three general categories of topics listed on the Hot Search based on a Weibo corpus[4]: entertainment, current affairs, and social events. We extracted the most popular topics from each category by summing the total engagement number and the duration and ranking on the Hot Search.

As a result, we identified three topics: (1) the Xiao Zhan 227 event (hereafter, 227) for entertainment, (2) the effectiveness of traditional Chinese medicine in treating COVID-19 (hereafter, TCM) for current affairs, and (3) the Black Lives Matter (hereafter, BLM) for social events. The 227 originated from an online gay fiction in which a male celebrity's (Xiao Zhan) image was altered as a female character in late February 2020. TCM originated from a press conference in late April 2020 in which a high profile Chinese medical scientist claimed that some Chinese traditional medicines were effective in killing the coronavirus. BLM originated from the global ethnic rights protection activities triggered by an incident in which a Black man was killed while being arrested in Minneapolis in the United States on May 25, 2020. These topics appeared on the Hot Search for a three-month period.

We followed a two-step approach to develop our empirical setup (see Appendix A). First, to conduct an initial screen, we used a Python script to identify relevant posts in bulk from the keywords and timestamps. Specifically, we used the keywords "Xiao Zhan," "traditional Chinese medicine," and "Black Lives Matter" to identify relevant posts that were included in the Hot Search. We then used Jieba (a Chinese word segmentation tool) and BosonNLP (a semantic lexicon) to categorize and score the content ideology of the Weibo posts [56,69]. Jieba allowed us to split a sentence into words and short

[3] See Statista: https://www.statista.com/topics/7863/social-media-use-during-coronavirus-covid-19-worldwide/
[4] The corpus we used was https://weibo.zhaoyizhe.com/. It is a digital archive that records Weibo hot events by topic, duration, and ranking on the Hot Search list, total engagement number, and time.

phrases, which avoided meaningless semantics (e.g., conjunctions and prepositions) that could interfere with the analysis. BosonNLP allowed us to validate captured semantics against a lexicon of emotionally charged semantics. Appendix B provides more information about the content ideology extraction. As a result, we identified a pool of 3,600 Weibo posts that were explicitly labelled as aggressive (e.g., “Xiao Zhan is shameless”), neutral (e.g., “Xiao Zhan be himself”), and constructive (e.g., “Xiao Zhan spreads positive energy”). Each author randomly selected 200 posts for each topic to ensure that the treatment of the content ideology was consistent. Although we acknowledge that our captured data might not correspond to all Weibo posts about the three topics, we believe that our captured data show an extensive and representative collection of content ideology because our sample topics covered events with high social attention on Weibo.

Second, after the dataset had been created, we conducted a survey to examine the hypotheses. We employed a survey because a survey method is an appropriate instrument for capturing people’s accurate cognitive recall and reflection of an item [70]. Specifically, we followed three criteria to select the nine posts for our survey design. First, we allocated three posts for each topic, representing different content ideology. The selected posts had to embrace the corresponding content ideology (in the form of semantic representations) and have the highest score for each semantic representation based on the results of the Jieba and BosonNLP analysis. Table 2 shows some examples. To ensure relevance, we did not include more posts for each topic because we needed to minimize potential effects from other factors, such as different accounts and publish dates. Second, to examine the moderating effect of functional affordances, all nine posts had to include functional affordances (i.e., @, #, and URL). Third, to examine the moderating effect of symbolic expressions and finalize our sampling, we selected those with the most obvious symbolic expressions (i.e., the highest numbers of likes, comments, and shares) in the remaining posts. Appendix C illustrates a sample of one selected post.

Table 2. Sample Posts with Illustrative Semantics

Topic	CI	Illustrative semantics from Weibo posts
	Agg.	'shameless', 'whole family die'
227	Neu.	'be myself in my life', 'never forget where I came from'
	Con.	'support and love', 'spread positive energy'
	Agg.	'ridiculous', 'bragging like a joke'
TCM	Neu.	'early research stage', 'clinical study'
	Con.	'obvious effectiveness', 'effectively antiviral'
	Agg.	'burst out conflicts', 'fired tear gas and flashbang'
BLM	Neu.	'appeal to uphold justice'
	Con.	'I feel sorry for him', 'I pray for him'

Keys: CI=Content ideology, Res.=Response, Agg.=Aggressive, Neu.=Neutral, Con.= Constructive

The original instrument of our survey was in English. We used a back-translation method [71] to develop a Mandarin version of our survey in consideration of the respondents whose first language was Mandarin. More specifically, one author translated the original questionnaire into Mandarin, and an independent senior scholar then translated the Mandarin version back into English. To ensure validity, all authors were engaged in an evaluation process to assess whether the translated survey conveyed the correct meanings of the items. We repeated the translating process until an agreement was reached. We designed the survey in three groups: one for each event. For each group, we screen-captured the selected three posts to represent different content ideology. Appendices C provides more information about our survey design. Further, to avoid the common method bias, based on Malhotra et al. [72], we followed two action suggestions: (1) the participants were anonymous and (2) the items in the survey were randomly arranged and the questions were presented to participants in random order.

We distributed a total of 693 web-based surveys to adults across China from December 5 to 10, 2020. Respondents were selected using probability sampling. Respondents were instructed to complete the survey only if they had a Weibo account. This mitigated the problem of respondents who were not aware of Weibo's basic functional offerings and symbols. Further, we used list-wise deletion to address missing cases found in the responses to estimated unbiased regression coefficients [73]. As a result, we received 468 usable responses, and the response rate was 67.53%. We collected at least 50 effective responses for each post. Table 3 shows the sample demographics of our survey samples.

Table 3. Sample Demographics

Characteristics	Levels	Frequency	Percentage (%)
Gender	Male	213	45.51
	Female	255	54.49
Age	<30	276	58.97
	30-39	161	34.40
	40-49	22	4.70
	50-59	7	1.50
	>59	2	0.43
Education background	≤Junior college	32	6.84
	Undergraduate	362	77.35
	Postgraduate	74	15.81
Experience of Weibo	<1 year	32	6.84
	1-3 years	85	18.16
	3-5 years	148	31.62
	5-10 years	175	37.39
	>10 years	28	5.98
Frequency of daily use	Never	38	8.12
	Occasional	77	16.45
	General	70	14.96
	Repeated	121	25.85
	Often	162	34.62
Total time of daily use	<0.5 hour	132	28.21
	0.5-1 hour	186	39.74
	1-3 hours	124	26.50
	3-5 hours	19	4.06
	>5 hours	7	1.50

4.2. Measures

We adapted scales from prior empirical studies to fit our empirical setup. Appendix D presents the measurement items and original sources. All variables were measured using a five-point Likert scale: 1 = Strongly Disagree, 2 = Disagree, 3 = Moderate, 4 = Strongly Agree, 5 = Strongly Agree. Specifically, following Lee et al. [74], we used absolute values of responses to capture *opinion polarization* (OP), measured by the question asking favorability about the Weibo post content. We applied single-item to measure opinion polarization because polarization is unidimensional to the respondent [75]. Further, our measurement of OP was in line with the literature on comprehension of opposing views, which describes polarity as people's attitudes and reflections (agreement and disagreement) on others' claims against their own claims [76].

We operationalized *content ideology* (CI) of the Weibo posts by asking the participants to rate the degree of aggressiveness (constructiveness) of what the post expressed, following Chen et al. [77]. Our measurement of CI was derived from the literature adopting a sentiment perspective to discuss and investigate reasons for online deliberation, which often accommodates emotionally charged words and descriptions [78]. The literature generally treats online content as sentiments that embrace "a positive or negative view, attitude, emotion, or appraisal about an entity or an aspect of the entity from an opinion holder" [33,56]. Accordingly, we collected and analyzed posts with aggressively, constructively, and neutrally charged sentiments to capture content ideology.

To examine the moderating effects, we used three items (i.e., @, #, and URL) to measure *functional affordances* (FA), adapted from Vaast et al. [20]. An example item is, "The post enables me to reach relevant tagging categorization through # (hashtag)." Similarly, we used three items (i.e., numbers of likes, comments, and shares) to measure *symbolic expressions* (SE), adapted from Lee et al. [79] and Oh et al. [80]. An example item is, “The post communicates me with its impact through the number of comments.”

We used gender, age, education background, experience, frequency of daily use, and total time of daily use as *control variables* [20,74,80]. Specifically, *gender* was measured as a dummy variable, *age* was measured by objective data, and scales of *education background* were measured in four categories (1 = secondary education, 2 = undergraduate, 3 = postgraduate, 4 = PhD). *Experience* was measured by the years of holding a Weibo account. *Frequency of daily use* was measured by how often the respondent used Weibo in a day. Total *time* of daily use was measured by estimated total hours using Weibo in a day.

5. Empirical Analysis and Results

5.1. Data Analysis

Before conducting the regression analysis, we tested reliability and validity of constructs (see Tables 4 and 5). The results indicated that factor loadings were larger than 0.70 in relevant items, and there were no high cross-loadings. Thus, the convergent validity was good. Table 4 shows that the values of Cronbach’s alpha, average variances extracted (AVE), and composite reliability (CR) of all factors exceeded 0.70. Thus, the construct reliability was good [81]. Table 5 reports the means, standard deviation, correlations, and the square roots of AVE scores for the main variables. The results indicated that all square roots of AVE (0.851–0.918) were larger than the correlation coefficients among the main variables (maximum value was 0.406), which demonstrated good discriminant validity [82,83].

Because all factors were measured using the same method, we conducted Harman’s single-factor test to examine the common method bias. The results indicated that no single factor accounted for the majority of the covariance, and the first unrotated factor only accounted for 36.188% of the total variance. Thus, common method bias was not an issue in this study [84].

Table 4. Construct Reliability

		Factor loading	Cronbach's alpha	CR	AVE
CI	CI1	0.951	0.901	0.951	0.906
	CI2	0.953			
FA	FA1	0.702	0.718	0.825	0.612
	FA2	0.822			
	FA3	0.817			
SE	SE1	0.872	0.805	0.870	0.690
	SE2	0.781			
	SE3	0.837			

Table 5. Descriptive Statistics and Discriminant Validity

	OP	CI	FA	SE
OP	—			
CI	0.160***	**0.952**		
FA	0.176***	0.078	**0.782**	
SE	0.147**	0.014	0.406***	**0.831**
Mean	0.722	3.129	3.494	3.996
Standard Deviation	0.519	1.052	0.842	0.717

Note: *p < 0.05, **p < 0.01, ***p < 0.001(2-tailed test). Entry on the diagonal with bold is the square roots of average variances extracted.

To test our hypotheses with moderating effects, we applied a hierarchical multiple regression method [85]. For the multi-item variables, we used the average of respondents' ratings of the relevant items. Table 6 presents the regression results. Specifically, following the procedure suggested by Aiken et al. [85], we regressed OP on CI and the control variables (gender, age, education background, experience, frequency of daily use, and total time of daily use) in Model 1. The results indicated that the equation was significant ($F = 5.478$, $P < 0.001$) and the relationship between CI and OP was positive and significant ($b = 0.077$, $p < 0.010$). Thus, **H1 was supported**, meaning that more extreme content ideology leads to stronger opinion polarization for a social media post. Except for gender ($b = -0.146$, $p < 0.010$) and age significance ($b = 0.114$, $p < 0.010$), the other control variables were insignificant.

Table 6. Results from Hierarchical Regression Analysis (N = 468)

	OP			
	Model 1 Coefficient (Standard Error)	Model 2 Coefficient (Standard Error)	Model 3 Coefficient (Standard Error)	Model 4 Coefficient (Standard Error)
Intercept	0.514** (0.181)	0.571 (0.344)	1.277** (0.491)	1.167* (0.515)
CI	0.077** (0.024)	-0.011 (0.092)	-0.279 (0.145)	-0.264 (0.150)
FA		-0.008 (0.088)		0.040 (0.083)
SE			-0.172 (0.111)	-0.176 (0.119)
CI×FA		0.024 (0.025)		-0.001 (0.027)
CI×SE			0.087* (0.035)	0.083* (0.038)
Gender	-0.146** (0.053)	-0.132** (0.053)	-0.145** (0.053)	-0.139** (0.053)
Age	0.114** (0.041)	0.096* (0.042)	0.109** (0.040)	0.100* (0.041)
Education background	0.038 (0.049)	0.046 (0.049)	0.043 (0.048)	0.047 (0.049)
Experience of Weibo	-0.011 (0.031)	-0.012 (0.031)	-0.017 (0.031)	-0.018 (0.031)
Frequency of daily use	0.005 (0.027)	0.000 (0.027)	-0.002 (0.027)	-0.004 (0.027)
Total time of daily use	0.042 (0.035)	0.038 (0.035)	0.039 (0.034)	0.039 (0.035)
F value	5.478***	4.912***	5.782***	4.830***
R^2	0.077	0.088	0.102	0.104
Adjust R^2	0.063	0.070	0.084	0.083
ΔR^2		0.011	0.025**	0.027**

Note: *p < 0.05, **p < 0.01, *** p < 0.001 (2-tailed test).

To test the moderating effect of FA, we incorporated FA and the interaction term (CI×FA) in Model 2 based on Model 1, which contained CI and six control variables. The equation was significant ($F = 4.912$, $P < 0.001$). The result indicated that the coefficients of the interaction terms (CI×FA: $b = 0.024$, $p > 0.050$) was insignificant. Thus, **H2 was not supported**, meaning that functional affordances do not have an interacting effect between content ideology and opinion polarization. Gender ($b = -0.132$, $p < 0.050$) and age ($b = 0.096$, $p < 0.050$) were significant, but the other variables were not significant.

To test the moderating effect of SE, we incorporated SE and the interaction term (CI×SE) in Model 3 based on Model 1. The result indicated that the equation was significant ($F = 5.782$, $P < 0.001$), and the coefficients of the interaction terms (CI×SE: $b = 0.087$, p < 0.050) were positive and significant. As Figure 2 shows, following Meyer et al. [86], we plotted the marginal effect of content ideology on OP at different levels of SE. We found that as the value of SE increased from 3.82 to 5.00 (accounting for 72.65% of the total sample size), the relationship between CI and OP became significantly stronger. Thus, **H3 was supported**, meaning that symbolic expressions positively moderate the relationship between content ideology and opinion polarization for a social media post. The significance of all other variables remained the same as Model 1.

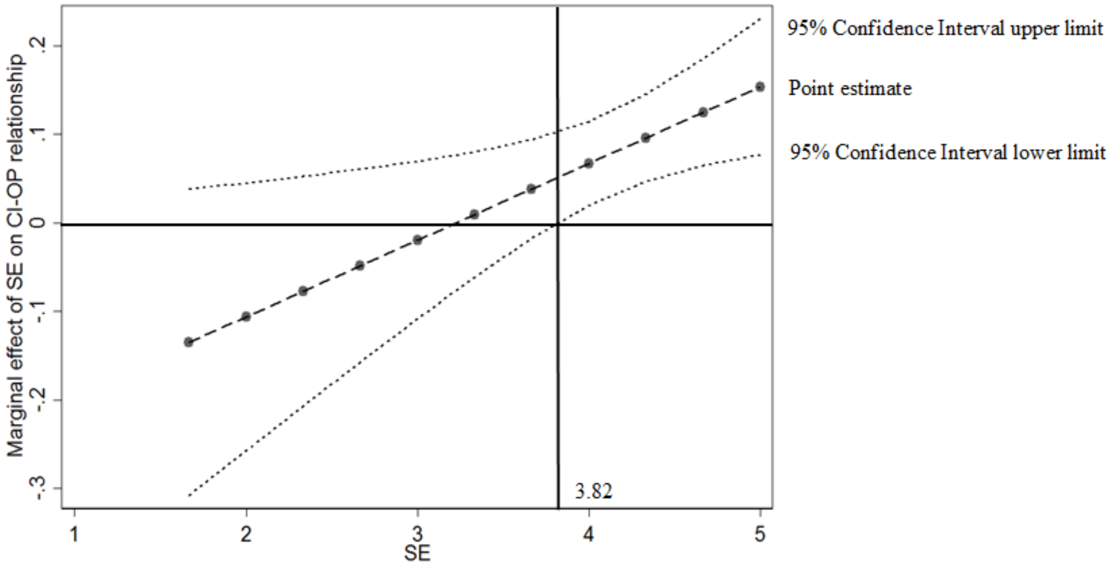

Figure 2. Moderating Effect of SE on the Relationship between CI and OP

5.2. Supplementary Analysis

To test the robustness of our regression results, we included the control variables (gender, age, education background, experience, frequency of daily use, and total time of daily use) in the regression on OP, as well as CI, FA, SE, CI×FA, and CI×SE in the full model (see Model 4 in Table 6). The results indicated that the coefficient of CI×FA ($b = -0.001$, $p > 0.050$) was insignificant, and the coefficient of CI×SE ($b = 0.083$, $p < 0.050$) was positive and significant, which was consistent with the results of Model 2 and Model 3. Thus, we found additional support for the interaction hypotheses.

To further test the robustness of our research model, we divided the sample into two subsamples according to high and low levels of SE (above mean value) and low (below mean value) and regressed the relationship between CI and OP. The results indicated that the slope was steeper in higher rather than lower levels of SE ($b_{High} = 0.100$, $p < 0.001$ vs. $b_{Low} = -0.018$, $p > 0.050$). These results were consistent with our expectations and hypotheses. Thus, our analysis and results were robust.

5.3. Empirical Analysis Synthesis

By analyzing the degree of content ideology reflected in different Weibo posts—namely, aggressive, neutral, and constructive—we showed that different content ideology influences opinion polarization differently. Specifically, opinion polarization is more likely to be generated when users sense more aggressive or more constructive content ideology from a post. Further, consistent with the insights from existing literature, symbolic expressions are positively associated with the effect of content ideology on opinion polarization. The positive moderating effect of symbolic expressions is evidenced by users' vastly different opinions about the same post when the post communicates a stronger influence (i.e., larger numbers of likes, comments, and shares).

However, contrary to the literature, our results do not support the view that social media functional affordances have a moderating effect between content ideology and opinion polarization. Based on our data analysis, although many users recognize the functional offerings (e.g., @, #, and URL) employed by a post, there was no change in their opinions about the focal post. One explanation is that only perceiving @, #, and URL is insufficient in having a moderating effect between content ideology and opinion polarization until these functional offerings have been actualized [52].

6. Discussion

Although the World Economic Forum has designated social media opinion polarization as a critical threat to digital and social harmony [6], it remains a persistent phenomenon on social media. Therefore, we explored explanations of opinion polarization.

Specifically, we developed and examined hypotheses that (1) content ideology can lead to social media opinion polarization, and (2) the effect of content ideology varies depending on the symbolic expressions communicated between the content and users. In the following sections, we discuss our contributions to research and practices, and highlight avenues for future research.

6.1. Implications for Research

This study makes several important contributions to the literature. First, it moves beyond the determinate role of echo chambers in inducing social media opinion polarization and contributes to the emerging literature that investigates the effect of online sentiments [12,33]. Studies have generally assumed that algorithmically created echo chambers intensify opinion polarization on social media [7,10,11], but some recent studies have called this assumption into question [12,16,34]. Kitchen et al. [14] conducted an inspiring study and proposed an alternative view by showing that online partisan polarization is a result of users' consumption of social media content, rather than simply a result of echo chambers. While Kitchen et al. [14] discussed the consuming-side influence (i.e., the consumption of social media content from different sources) on partisan shifts and polarization, our study examined the creating-side influence (i.e., the ideological representation of social media content) on opinion polarization in general. To our knowledge, our study is the first attempt to directly link social media opinion polarization with content ideology. The results show that opinion polarization is more likely to occur when social media users sense strong ideological preferences embedded in the content, regardless of the information source.

Second, our study extends the literature on social media opinion polarization to the topic of functional affordances and symbolic expressions. As discussed, such polarization has mostly been studied as a consequence of users' exposure to likeminded content [9] (the echo chamber view) or "toxic" content [34] (the sentiment view). Such views overlook how social media design may moderate these consequences. Ignoring the moderating role of social media design is problematic because people can also choose to read likeminded or toxic content from traditional paper-based press. To address this issue, we are among the first to empirically examine functional affordances and symbolic expressions as key social media design factors that may moderate opinion polarization. Functional affordances and symbolic expressions accommodate how social media delivers and communicates content to users [19,20]. Specifically, we observed more intense opinion polarization when social media communicated stronger symbolic expressions in the form of quantified engagement signals. However, we did not find a significant moderating effect of functional affordances as the literature suggested. Our findings suggest that the effectiveness of functional affordances cannot be determined without identifying whether the affordances are perceived or actualized because people's opinions about a post will not change until affordances are both perceived and actualized [52].

Finally, we advance the literature by expanding social media opinion polarization to topics broader than political discourses. The literature has generally treated opinion polarization as a phenomenon associated with political slants [12] and partisan shifts [14]. Although this treatment captures an important aspect of users' engagement with social media—especially microblogging [76]—it overlooks the pluralistic nature of social media opinion polarization. Our study complements the literature by showing that opinion polarization is not only a result of political discourses on social media, but also an issue observed under wider topics such as entertainment, current affairs, and social events. Thus, our study provides a plausible explanation for opinion polarization as a broad concern on social media [6], because trending event ranking (e.g., “Hot Search” on Weibo and “trends” on Twitter) covers more diverse topics than political discourses [87], where opinion polarization is more likely to occur [3].

6.2. Implications for Practice

This study has important practical implications. First, as a result of social media taking over the role of traditional paper-based presses relating to information dissemination, social media opinion polarization has become a major concern as a digital and social risk [4,6]. Thus, understanding how social media content affects opinion polarization is vitally important to online regulatory bodies. Specifically, our finding of the direct causal relationship between content ideology and opinion polarization suggests that some individuals and firms can embed extreme content ideology in posts to increase the intensity of discussion and improve marketing effectiveness. Our study suggests that online regulatory bodies can use content ideology as an indicator to detect cyberviolence and implement interventions (e.g., reminding sensitive semantic content) to control the spreading of posts with extreme content ideology.

Second, our study has important implications for social media designers. Our results imply that heterogeneity exists in the effect of content ideology and social media opinion polarization. Specifically, the effect is greater for posts that communicate stronger signals of influence, which suggests that social media designers should pay more attention to monitoring symbolic expressions. For example, social media designers should implement interventions such as hiding the number of reposts, comments, and likes to prevent sharp opinion polarization for certain content—especially content on the trending event ranking. For example, YouTube makes the number of likes visible but hides the number of dislikes, which creates a positive online environment.

6.3. Limitations and Future Research

Because this study is based on a single platform (i.e., Weibo) of a particular type of social media (i.e., microblogging), it is necessary to consider limitations to the generalizability of the results. While it is not possible to definitively rule it out, there is no reason to assume that the empirical findings from Weibo are atypical of other social media because the variables being examined are used across most platforms of different types of social media. The other limitation stems from constraints resulting from the survey approach. Specifically, we were unable to capture all of Weibo's functional affordances and symbolic expressions in the survey questionnaires. We addressed this by using items that have been both well-examined in the literature and widely applied by social media platforms as our measurement.

We encourage future research to expand our study by considering other social media factors that may influence how content ideology affects opinion polarization. While it is plausible that symbolic expressions can moderate the degree of social media polarization, assuming that these symbolic expressions are designed in the same way across different social media layouts may lead to inaccurate conclusions. Relatedly, our findings are based on the typical layout of symbolic expressions. That is, the numbers of social media engagements are presented below a post. This suggests an opportunity for future research to consider other layouts of symbolic expressions (and functional affordances). For example, Facebook once introduced a "dislike" symbol but decided to remove it because people used it to express contempt rather than empathy.

Another profitable direction for future research is to further unpack the mechanisms driving social media opinion polarization. We assume that social media users may not form extreme opinions (when these opinions are contradictory, they are polarized) immediately after reading the content. Conditions (e.g., the extent to which a person is familiar with the content) and processes (e.g., different stages of opinion formation) for social media opinion polarization may exist. While we find that content ideology and symbolic expressions are important antecedents and moderators of opinion polarization, our data do not allow us to isolate the mechanisms driving these findings. Thus, a promising future avenue may be to further explore these mechanisms.

7. Conclusion

The question of how content on social media induces opinion polarization is crucial to society in the digital era. Our study provides a much-needed investigation of social media opinion polarization, supported by insights obtained from users' reactions to different posts with different content ideology, and interacting with the intervention of functional affordances and symbolic expressions. As inspired by the emerging sentiment perspective of such polarization, we found a strong causal effect of a post's content ideology, which complements the literature on social media polarization that explores other antecedents than echo chambers. Our findings also lead to new research opportunities. Specifically, there is a strong need for future research to focus on the role of social media design in inducing and moderating opinion polarization, because to develop native theory for IS phenomena, we should focus more on IS characteristics (e.g., functional affordances and symbolic expressions). Our study provides instrumental insights for online regulatory bodies and social media designers to detect and mitigate the digital and social risks of social media opinion polarization.

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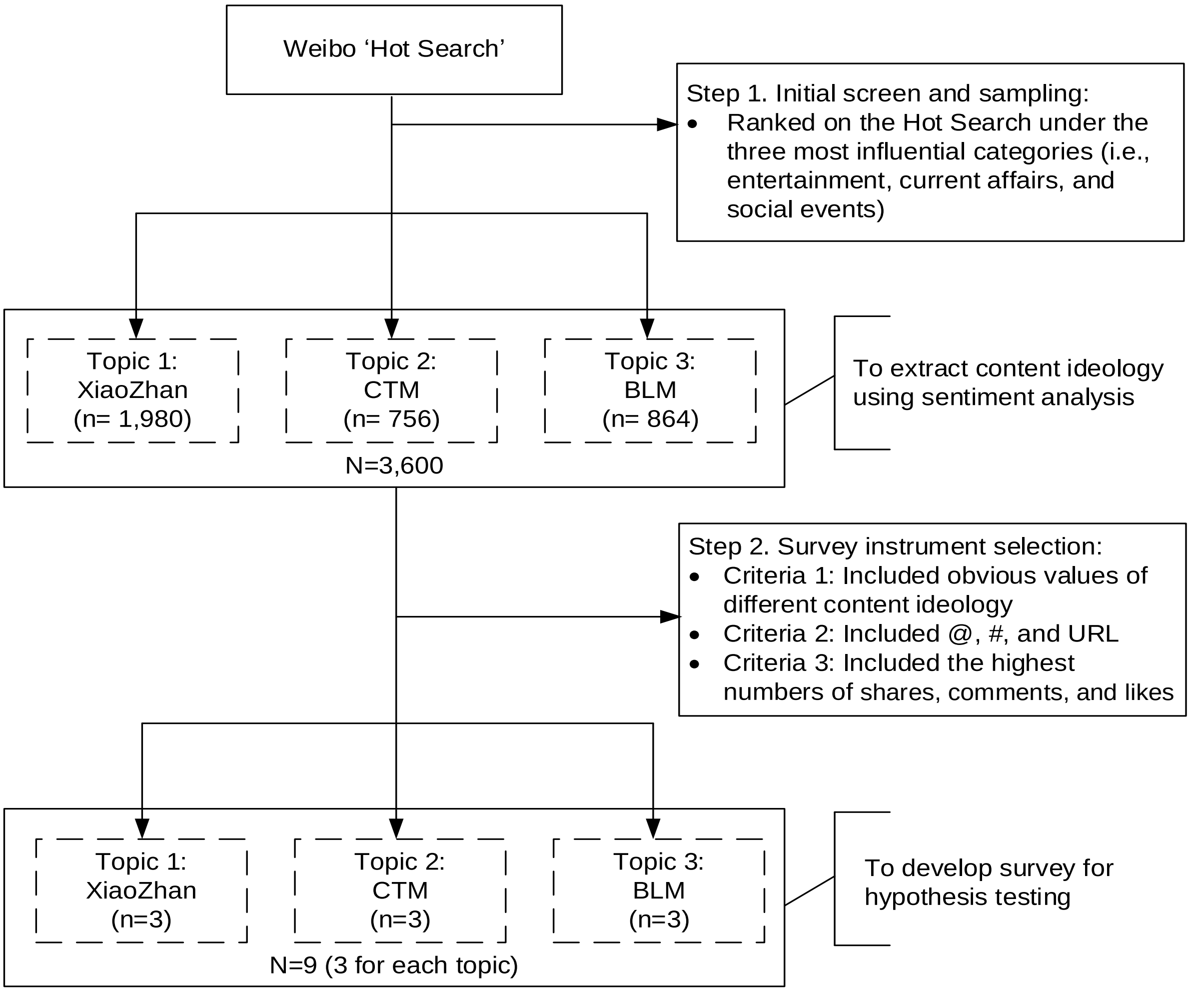
Appendix A. Weibo Posts Selection Process

Please find below our sampling for content ideology extraction and our instrument development for survey design.



Appendix B. An Illustration of Content Ideology Extraction

In general, we used Jieba to reduce the irrelevant semantics in Weibo content and to improve the number and density of keywords. To illustrate, we captured the core part of the code scheme

```
Post_sentiment = []
for string in df['Post content']:
    words = jieba.lcut(str(string))
    words_vec = sum_vec(words)
    model = joblib.load('dt_model.pkl')
    result = model.predict(words_vec)
  Post_sentiment.append(result[0])
```

We used algorithm (1) to weigh words with different ideological intensity.

$$\bar{E} = \frac{\sum_{i=1}^{N_a} wp_i + \sum_{j=1}^{N_c} wp_j}{N_a + N_c} \qquad (1)$$

N_a, N_c represents the number of words expressing aggressive and constructive semantics respectively. wp_i, wp_j represents the weights of aggressive and constructive semantics respectively. In general, a weighted result of (-1) is aggressive, and a negative result of (1) is constructive, and a result of zero (0) is neutral.

Further, we used the BosonNLP polarity dictionary to validate the semantic analysis result. BosonNLP contains a dictionary of 114,767 commonly used words assigned as aggressiveness or constructiveness. To illustrate our validating process, we captured the core part of the code scheme

```
def word_cut(x): return jieba.lcut(x)
con['words'] = con[0].apply(word_cut)
agg['words'] = agg[0].apply(word_cut)
x = np.concatenate((con['words'], agg['words']))
y = np.concatenate((np.con ones(len(pos)), np. agg ones(len(neg))))
np.save('X_train.npy', x)
np.save('y_train.npy', y)
```

Appendix C. An Illustration of Functional Affordances and Symbolic Expressions

Appendix D. Questionnaire Items

Construct	Items	Sources
Opinion polarisation (OP)	(OP) I support what the post describes.	Lee et al. (2014)
Content ideology (CI)	(CI1) The post uses aggressive terms to describe the event.	Chen et al. (2012)
	(CI2) In general, I would describe the post as aggressive.	
Functional affordances (FA)	(FA1) The post enables me to reach relevant accounts and people through @.	Vaast et al. (2017)
	(FA2) The post enables me to reach relevant tagging categorisation through #.	
	(FA3) The post enables me to gain more comprehensive information through URL.	
Symbolic expressions (SE)	(SE1) The post communicates me with its impact through the number of reposts.	Lee et al. (2018), Oh et al. (2017)
	(SE2) The post communicates me with its impact through the number of comments.	
	(SE3) The post communicates me with its impact through the number of likes.	