Understanding Users’ Group Behavioral Decisions About Sharing Articles in Social Media: An Elaboration Likelihood Model Perspective

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Abstract
The decision to share information is a common phenomenon in individuals’ daily social media use (e.g., Twitter, micro-blogs). However, research on the information to be shared mainly focuses on short texts, and the research on long texts/article sharing is relatively limited. Based on the elaboration likelihood model (ELM), this study established a conceptual model to reveal the determinants of users’ behavior in sharing articles. Data on 1311 articles were collected on WeChat, China’s most popular social media, and were processed using multiple linear regression. We found that both the central path and the peripheral path of the ELM affect users’ decision-making about article-sharing behavior, and that amount of reading and perceived usefulness have the greatest impact. The rhetorical title, the number of pictures, and the number of fans have a negative impact on users’ decision-making about article-sharing behavior. Further, the factors that affect users’ online-community sharing and sharing with friends are also different. This study is one of the first to apply ELM to examine the influencing factors of users’ decisions about sharing general articles on social media, contributing to the research on the decision-making behavior of users sharing long texts on social media.

Keywords Article sharing · Social media · WeChat · Elaboration likelihood model · Behavior decision

1 Introduction
Social media greatly enhances public access to all kind of information, such as news, essays, and friends’ activities; it has become an important information source and facilitates the information dissemination process (Shi et al. 2018). Sharing
Information on social media is a common behavior (Tseng et al. 2017). For example, when users see something interesting or beneficial, they like to share it with friends or an online community, as illustrated in Fig. 1. If a message gets the attention of enough people, there could be a social epidemic. Brands and retailers often take advantage of this phenomenon to promote their products and services; some have succeeded, while others failed (Berger and Milkman 2012).

Many researchers have explored the mechanism of users’ sharing of short texts on some popular platforms (e.g., Twitter and Weibo) from several perspectives. Content-related factors, such as emotional tone (Eckler and Bolls 2011; Park and Kaye 2019), the number of visual messages (Park and Kaye 2019; Ordenes et al. 2019), and information quality (Zhang et al. 2017) have been identified as significantly affecting users’ message-sharing decisions. Source-related or author-related factors such as source credibility (Westerman et al. 2014; Lu et al. 2021) and source attractiveness (Liu et al. 2012) are also found to have an impact on users’ sharing-behavior decisions, along with recipient-related factors such as the impact of social tie strength (Choi et al. 2017), life satisfaction, and internet satisfaction (Hsiao 2020). A relatively complete theoretical framework has been proposed to explain the various factors under which users spread information on social networks (Shi et al. 2018).

At present, there is no clear definition of long texts, only relative concepts of short and long, but word count is undeniably the most important basis to distinguish long from short texts. Twitter users are limited to 280 characters, and Weibo users are limited to 140 characters. Both platforms are mainstream, sharing popular social media with user posts. In China, WeChat provides a good social platform for sharing long articles. Zhang Xiaolong, vice president of Tencent and founder of WeChat, has said that 1.09 billion users open WeChat every day, 780 million enter Moments, 120 million post Moments, and 360 million read official articles (long texts) in a public speaking. Sharing official account content with Moments is a way for users to share articles on WeChat. Therefore, with its large number of users, WeChat is a persuasive
platform choice for examining article-sharing behavior decisions on social media. This study used several WeChat Official Accounts (WOAs) and their articles to conduct the experiments.

Regarding long texts, existing research about sharing-behavior decisions mainly focuses on news texts (Lee and Ma 2012; Su et al. 2019; Apuke and Omar 2020; Thompson et al. 2020). To the best of our knowledge, few researchers have studied general long texts, such as movie reviews, life stories, and introductions to practical skills. In this digital age, people do most of their reading online (Kurata et al. 2017), especially on social media. Compared with short texts, long texts always convey richer meaning and connotation (Deng et al. 2021). Long texts, including e-journals, e-books, e-magazines, and e-newspapers are becoming increasingly popular for their convenience and lack of cost (Tarkiainen et al. 2009; Graham and Greenhill 2013). Meanwhile, publishing long-form content on social media is an essential content marketing tactic, like storytelling (Pulizzi 2012; Holliman and Rowley 2014). Therefore, studying the sharing of long texts not only fills a gap in current academic research but also helps provide guidance for relevant media to publish articles.

This study proposes a conceptual model that integrates factors influencing users’ article-sharing behavior decisions on social media. Specifically, three research questions are examined:

**Research question 1 (RQ1):** What are the determinants of users’ article-sharing behavior decisions on social media?

**Research question 2 (RQ2):** Which factors are the most influential?

**Research question 3 (RQ3):** Do different factors affect users’ sharing-behavior decisions in different channels?

The elaboration likelihood model (ELM) can help provide a thorough understanding of users’ information-sharing behavior (Petty and Cacioppo 1986). Focusing on the influence process and classifying the influence mechanisms into central and peripheral routes, the ELM can explain individual’s reactions to online content. Thus, it allows us to explore users’ sharing-behavior decisions from the perspective of a sharing-decision-maker. As a decision-maker, the user may follow the central route, such as the article’s depth and practicality, and rely on peripheral cues such as source credibility, the quantity of reading, and the number of likes. This theoretical framework provides a lens for understanding the influence process of users’ article-sharing decision-making.

The reminder of this paper is organized as follows. Section 2 reviews the previous related literature and discusses its limitations. Section 3 introduces the research model and hypotheses. Section 4 introduces the research data corpus and the variables being tested. In Sect. 5, the model for data analysis and results are presented. Section 6 summarizes the key findings and discusses the implications for both research and practice, the limitations, and future research directions.
2 Literature Review

2.1 Social Media and Information Diffusion

Social media’s popularity has earned it increasing scholarly attention, and it has been given multiple definitions (Kaplan and Haenlein 2010; Kapoor et al. 2018; Pivec and Maček 2019) aimed at clarifying the concept. Although expressed differently, these definitions complement each other. In this paper, it refers to online platforms where users have access to digital content and social relationships. It is worth noting that social media’s positive influence on information diffusion is often mentioned in the literature. According to previous studies, information diffusion on social media is affected by at least four types of factors: external factors, social influences, personal attributes, and information characteristics (Crane and Sornette 2008; Wang and Zhu 2021). A lot of research is carried out from these aspects. For example, from the message features and network characteristics, Meng et al. (2018) analyzed the determinants influencing the size and structural virality of information diffusion on Twitter. Several information diffusion models have been proposed and applied. For instance, Yoo et al. (2019) formulated a generalized version of the self-exciting point process model to study how the diffusion of a given piece of content is influenced by the diffusion of other cascades carrying similar content. Information sharing is an important method of information diffusion (Wang and Zhu 2021), and has been a focus of research in recent years.

2.2 Behavioral Decisions on Social Media

Behavioral decision-making means that people with limited rationality are subject to their own cognitive level and are influenced by perceptual deviations to make satisfactory decisions.

With regard to social media decision-making, many scholars have studied the role of publishing and disseminating information on social media for decision-making in a specific field. Azeez (2021) reported that sharing information such as article reviews on social media can greatly affect tourism decision-making. This kind of travel decision, which relies on information from social media, covers every aspect of the trip. Robinson and Robinson (2021) found that educators’ use of social media helps students make more informed decisions and promotes their all-round development. With regard to the research on behavioral decision-making on social media, Lesser et al. (2021) believe that the use of relevant social information will promote the initiation of preferences when choosing leisure activities, thus enhancing the group process. Gupta et al. (2021) studied the impact of the combination of consumer attitudes and social media on consumers’ purchasing behavior decisions. Wang et al. (2021) identified travelers’ characteristic preferences according to some evaluations on social media, and formed a hotel recommendation list according to these preferences, providing guidance for hotel management strategies and travelers’ decisions.
2.3 Information Sharing on Social Media

Information sharing on social media is a social communication process. From this perspective (Hovland 1948), communication is a process where the information source (the information carrier, such as a message or an article) transmits stimuli to modify the behavior of the information recipients (Zhang et al. 2014; Shan et al. 2017; Shi 2018). Applying this view to users’ sharing-behavior decisions in social media, we can roughly divide the existing studies into several categories.

The first category focuses on the impact of the information carrier. Some research has focused on sentiment (Stieglitz and Dang-Xuan 2013; Zhu et al. 2020), some examines characteristics of the message. For example, Lahuerta-Otero et al. (2018) examined tweet length, sentiment, links, mentions, and hashtags under several purchase involvement situations. Ordenes et al. (2019) proposed that rhetorical styles, cross-message compositions, and the presence of visuals influence consumers’ sharing on Facebook and Twitter.

The second category focuses on the characteristics of both the information source and information carrier. For example, Liu et al. (2012) analyzed the determinants of information retweeting in emergency events and found that characteristics of both the information source (including source trustworthiness, source expertise, source attractiveness) and the information carrier (including content comprehensiveness and content objectivity) had positive effects on the number of retweets based on data containing 360,000 Sina micro-blogs.

The third category focuses on the characteristics of the recipient, including gratification, social capital, and social cognitive process (Ho and Dempsey 2010; Lee and Ma 2012). Matching and involvement have also been studied (Rudat and Buder 2015; Zhang et al. 2017; Yin et al. 2020), emphasizing the matching of information and users in message rebroadcasting. In addition, the relationships between the information source and the recipient have also been considered. Social tie strength (Shi et al. 2014; Zhang and Wang 2019), community structures (Harrigan et al. 2012; Luarn et al. 2014; Milani et al. 2020), homophily (Ma et al. 2014; Keyzer et al., 2019), and so on, have been given much attention.

The previous literature on information sharing suggests that most studies focused on short texts, although some focused on the dissemination of news, natural disaster information, and health information. The scope of prior studies on the determinants of users’ article sharing is large, and little has been done. Furthermore, little is known about the differences among the factors affecting sharing to different channels. However, this information is important for both academic and practical purposes. With long texts being the complementarity of short texts, it necessary to pay attention to long texts when studying texts in social media, to better explore users’ reading behavior. Furthermore, long texts are more expressive than short texts, making them more suitable for media companies and practitioners to obtain traffic through content marketing.
2.4 Elaboration Likelihood Model

The ELM interprets how information processing influences individuals’ information decision-making process (Petty and Cacioppo 1986) and provides insights into their information. The ELM divides the process in which individuals engage with information into central and peripheral routes (Petty and Cacioppo 1986). The first is information-centric, and an effortful and thoughtful assessment of the core values of the argument is needed. The second focuses on peripheral cues, rather than the content itself, and requires less cognitive effort to evaluate the information. The central route manifests when recipients need to read and analyze the information carefully, indicating a high level of elaboration likelihood to recipients. The peripheral route occurs when using simple references to evaluate the information, such as popularity, source credibility, and celebrities. The central and peripheral routes are a theoretical division; however, in practice, information processing may involve a mixture of these routes (Petty and Cacioppo 1986).

The ELM is often used in information-related decision-making processes, and prior research shows that information processing behavior is a key point influencing individual decision outcomes (Cheung et al. 2008; Sutton et al. 2015; Yu et al. 2019; Deng et al. 2020). The premise for sharing an article is that users need to read it and process the information contained within. Sharing can be viewed as a behavioral decision made after assessing a particular article. The behavior of sharing is the result of users’ information decision-making process. Moreover, the influencing factors can be divided into two routes; thus, the ELM is applicable.

3 Research Model and Hypotheses

3.1 Research Model

The research model is based on the ELM and prior research, and is presented in Fig. 2. We posit that users’ information processing in the central and peripheral routes contributes to article sharing, and classify the relevant factors into the two routes. Control variables, release time, and release position are included in our model, because the ELM is closely related to individual thinking initiative. As objective factors, release time and release location do not belong to either of the two routes in the ELM and must be considered as control variables.

3.2 Routes and Hypotheses

3.2.1 Factors and Hypotheses on the Central Route

According to information processing theory (Miller 1956), individuals have limited ability to process all the information they are exposed to and perceive in their environment. The headline is the first thing users see, and most titles use rhetoric to
engage them (Zhang et al. 2020). Thus, we include title rhetoric in the central route. Article richness (Tseng et al. 2017; Park and Kaye 2019; Ordenes et al. 2019) and emotional tone (Eckler and Bolls 2011; Stieglitz and Dang-Xuan 2013; Zhu et al. 2020) have also been identified as determinants; thus, they also belong to the central route. Additionally, the usefulness of article information has been considered a significant factor in prior studies (Aghakhani et al. 2020; Shang et al. 2020). Usually, when a user sees something useful, the message will be flagged. Correspondingly, users in WeChat can click the “add to favorites” button, and the article is collected for easy future reference. Since usefulness is difficult to measure, this study uses the number of people who flag to measure it indirectly and consider it another central factor in the concept model.

Just like reading an article on a web page, the first thing users see is the article’s title. If the title is sufficiently attractive, users will click to read it and then share, probably with their emotions quickly stimulated, which can be explained by the information-gap theory of curiosity (Loewenstein 1994). Because rhetoric use is now common, article-title rhetoric is key for attracting users (Zhang et al. 2020). Due to the limitations of mobile devices, the article title is the first thing users see when they enter the second- and third-level pages of WeChat; only after clicking twice can they see the full text and forward the article. That is, WOAs limit the ability to forward articles directly without reading them. The related hypothesis is as follows:

**H1** The article-title rhetoric has a positive impact on users’ article-sharing on social media.

Many scholars have identified multimedia, such as the presence of visuals, links, and hashtags as influencing consumers’ sharing (Lahuerta-Otero et al. 2018; Ordenes et al. 2019; Park and Kaye 2019). We also uphold such a view in the official account articles; thus, another hypothesis is proposed.
**H2** Article richness has a positive impact on users’ article-sharing on social media.

Researchers have found that the quality of message content has a significant impact on message rebroadcasting (Ha and Ahn 2011; Zhang et al. 2017); individual perceived usefulness may increase the likelihood of article sharing (Aghakhani et al. 2020; Shang et al. 2020). Thus, we propose the following hypothesis:

**H3** Perceived usefulness has a positive impact on users’ article-sharing on social media.

Prior studies indicate that tweets containing emotional tone tend to be retweeted more often and faster than those with a neutral tone (Eckler and Bolls 2011; Stieglitz and Dang-Xuan 2013; Park and Kaye 2019). Considering the word limits, Twitter and Weibo posts are shorter than the articles in WOAs, and the effect of emotional expression is consequently less pronounced. We believe that the previously observed effects are still present and may be more pronounced. Therefore, the following hypothesis is proposed.

**H4** Emotional tone has a positive impact on users’ article-sharing on social media.

### 3.2.2 Factors and Hypotheses on the Peripheral Route

According to the ELM, the peripheral route typically influences individuals through simple decision criteria and cues, such as source credibility (Ha and Ahn 2011; Westerman et al. 2014; Lu et al. 2021), the number of followers (Suh et al. 2010; Peng et al. 2018; Park and Kaye 2019), source trustworthiness, and attractiveness (Liu et al. 2012; Westerman et al. 2014; Lu et al. 2021). Prior research has verified the impacts of these factors. Meanwhile, other users’ behaviors indicating a message’s popularity (the number of times read, likes, and comments) could affect individual behavior (Rudat and Buder 2015).

Source trustworthiness and source attractiveness have been mentioned frequently in prior literature about information sharing (Ha and Ahn 2011; Park and Kaye 2019; Lu et al. 2021). These two factors are often seen in applications of the ELM (Ha and Ahn 2011; Shi et al. 2018; Shang et al. 2018). In article-sharing, these factors are included in the peripheral route without exception. The related hypotheses are as follows.

**H5** Source trustworthiness has a positive impact on users’ article-sharing on social media.

**H6** Source attractiveness has a positive impact on users’ article-sharing on social media.

After an article is published, users can read it, give it a thumbs-up, and comment on it, and all users can see the data. These behaviors show the extent to which the article is accepted by the public (Rudat and Buder 2015; Shi et al. 2018). For example, an article that has been read and liked over ten thousand times will generally be
more accepted and shared by users than an article whose reads and likes are only over one hundred. Hence, we propose the following hypothesis:

**H7** The quantities of reads, liking, and comments, termed “informational social influence,” have a positive impact on users’ article-sharing on social media.

### 4 Data Collection and Variables Description

#### 4.1 Data Collection

WeChat, the most popular social media in China, has an important component—WOAs. Official accounts can be divided into service accounts and subscription accounts; subscription accounts push articles. For convenience, later in this paper, we refer to WOAs as subscription accounts. WeChat users often spend much time reading articles pushed from WOAs, and they often share articles with their friends or to Moments. There are two main paths for users to share articles in WOAs (Figs. 3 and 4). Clicking on the parts indicated by the red squares step by step shows the options for sharing. The first path (Fig. 3) involves clicking on “Subscriptions” on the WeChat homepage, which contains articles published by various public accounts, allowing users to click on and read push articles from subscription accounts. There are “Share” buttons at the bottom of the articles, which can be clicked to share on Moments or with friends. The other path (Fig. 4) involves going to the WeChat “Contacts” page and clicking on “Official Accounts,” which lists the various official accounts that users follow. From there, users can choose the official

![Fig. 3 Entrance 1 to subscriptions](image-url)
account they are interested in and read the articles in it. Articles are shared in the same way as above. In “Subscriptions,” articles are sorted and updated in chronological order, while in “Official Accounts,” users choose their favorite public accounts. Apart from the convenience of the first method, there is not much of a difference between them.

We selected 13 WOAs, which generated 1311 articles from March 1, 2019 to October 31, 2019. These WOAs have good operating conditions; that is to say, they have a certain number of fans, high frequency of pushing articles, and cover a wide range of fields. The number of fans of these official accounts ranged from 10,000 to 1 million, and the types of WOAs included entertainment, health, and so on.

4.2 Variable Descriptions and Measurement

4.2.1 Dependent Variable

The number of times an article was shared was the dependent variable in this study. Considering that articles in WeChat can either be shared on Moments or shared with friends, we defined three dependent variables: the total number of shares, the number of shares on Moments, and the number of shares with friends.

4.2.2 Independent Variables

(1) Article-title rhetoric: An article’s title will influence users’ decision to read and share it; hyperbole, insinuation, and visual rhetoric entice users to click the baited headlines (Zhang et al. 2020). In this paper, titles are divided into four types: direct, which directly expresses the topic; rhetorical, which uses questioning expressions; exaggerated, which conveys exaggerated exclamations; and
incomplete, which deliberately omits important information to create suspense. Ten juniors and seniors in Renmin University of China were recruited to complete the evaluation work, and were offered a reward of 200 ¥ for careful completion. Two students marked each article. We asked them to distinguish between the four types of rhetoric in the title. If there was a dispute, it was reassigned; if there was a dispute even after reassignment, the article was dropped.

(2) Article richness: pictures are the main form of multimedia in articles on WOAs. In this paper, the number of pictures in the article is used as a factor influencing article sharing.

(3) Perceived usefulness: according to the literature, there are few articles proposing a framework to evaluate articles’ usefulness in WOAs. It is not appropriate to evaluate articles directly. Instead, we used the number of people who collect articles to indirectly evaluate usefulness. The more people who collect an article, the more useful it should be.

(4) Emotional tone: most previous studies (Eckler and Bolls 2011; Stieglitz and Dang-Xuan 2013; Park and Kaye 2019) on articles’ emotional tone are based on sentiment analysis. Sentiment analysis of short texts is now applied to maturity, and algorithms are currently in development for long texts. Based on the considerations of accuracy and convenience, we take the results of manual evaluation. The previously-mentioned college students also helped judge the articles’ emotional tone. When the text quality is evaluated manually, its emotional tendency is also given. The measure was defined within the range \([-4, 4]\). Scores \(2, 3, 4\) denoted positive sentiment. Scores \((-2, -3, -4)\) denoted negative sentiment. Scores \((1, 0, -1)\) denoted neutral sentiment. As in assessing article quality, each article was assigned to two students. If the scores differed by more than 2, the article was reassigned; otherwise, the average was taken.

(5) Source trustworthiness: Source trustworthiness refers to the extent to which the information source is perceived to be trustworthy by information recipients (Petty and Cacioppo 1986), and indicates a message source’s level of reliability for correct and true information (Kelman & Hovland 1953). A relative reference system was used to determine the trustworthiness of information sources by reasoning on their knowledgeability, popularity, and reputation (Davide and Giuseppe 2019). To ensure the authenticity and security of the official account information, the WeChat platform provides an authentication service, which is the most important way WeChat ensures the credibility of article sources. The credibility of authenticated accounts is stronger than that of unauthenticated accounts, and the trustworthiness of the former will be stronger than that of the latter. Whether an official account has been certified is the standard for judging its trustworthiness. Authentication, termed as being "wx_certified," is taken as the index for measuring source trustworthiness in this paper. \(\text{Wx\_certified} = 1\) if certified by WeChat, or \(\text{wx\_certified} = 0\) if an account is uncertified.

(6) Source attractiveness: source attraction refers to the degree of popularity and liking by users (Petty and Cacioppo 1986). In WeChat, source attractiveness can be measured through the number of followers. The more followers an account has, the more attractive it is.
(7) Informational social influence: We used the numbers of times articles were read, liked, and commented on to describe the informational social influence.

4.2.3 Control variables

(1) Release time: Research shows that the release time for some news is crucial for assisting users’ decision-making in response to unanticipated conditions (Hu 2007). When a WOA pushes at the right time, its articles are more likely to be read and forwarded; people’s status is different on working days and non-working days, which might affect whether a given user reads or shares an article.

(2) Release position: Each WOA can only push messages once a day, and each push is limited to six items at most, the first of which are headlines. Not only are headlines the first things pushed, but their card displays magnify the cover pictures, making them more attractive. Considering the collected data, the release position is divided to reflect these two aspects.

The summary of all relevant variables is shown in Table 1.

4.2.4 Data Processing and Summary Statistics

We collected article data published by 13 WOAs over 6 months. Among the articles, we eliminated those with obvious advertising attributes, removed some extreme values caused by various reasons, and balanced the number of articles on various official accounts. Then we invited some college students to help us make judgments about the sentiment and the title rhetoric.

The summary statistics of all relevant variables are presented in Table 2. We checked for multicollinearity using STATA. All the VIFs were no bigger than 10, suggesting that multicollinearity was not a problem.

5 Methodology and Results

5.1 Regression Model

The dependent variable, the number of article shares, is a continuous variable. In the present research, multiple linear regression was adopted to analyze the data. The regression model was proposed as following:

\[
\frac{share_{total}}{share_{net}}/\frac{share_{user}}{\epsilon_i + x_i\beta = \epsilon_i + x_i\beta} \tag{1}
\]

\[
x_i = [title_type_i, img_n_i, favor_n_i, emo_tone_i, wx_ce_i,
fol_n_i, read_n_i, like_n_i, com_n_i, rel_t_i, rel_p_i] \tag{2}
\]

\(x_i\) is a vector of regressors with lags. \(\beta\) is a vector of coefficients. \(\epsilon_i\) is the dynastic individual effect. The subscript \(i\) refers to the \(i\) th article.
| Table 1: Variable Description | Description | Theoretical background |
|-------------------------------|-------------|------------------------|
| **Dependent variable** | Users’ sharing-behavior decision | Ordenes et al. (2019), Zhang et al. (2020), etc |
| share_total | Total number of article shares | |
| share_net | The number of articles shared on Moments | Lahuerta-Otero et al. (2018), etc |
| share_user | The number of articles shared with friends | Shang et al. (2020), etc |
| **Independent variables** | Title rhetoric | Siegliz and Dang-Xuan (2013), Zhu et al. (2020), etc |
| title_type | Categories 1–4 correspond, respectively, to direct, questions, exaggerations, and abrupt stops | |
| **Independent variables** | Article richness | Westerman et al. (2014), etc |
| img_n | The number of pictures in the article | Peng et al. (2018), etc |
| **Independent variables** | Perceived usefulness | Rudat and Budé (2015), Shi et al. (2018), etc |
| favor_n | The number of people who collect articles | |
| **Independent variables** | Emotional tone | |
| emo_tone | Emotional tendency of the text. Categories 1–3 correspond, in order, to positive, negative, neutral | |
| **Independent variables** | Source trustworthiness | |
| wx_ce | Whether account is certified or not | |
| **Independent variables** | Source attractiveness | |
| fol_n | The number of followers | |
| **Independent variables** | Informational social influence | |
| read_n | The quantity of reading | |
| like_n | The number of likes | |
| com_n | The number of comments | |
| Variable name  | Description                              | Theoretical background                      |
|----------------|------------------------------------------|---------------------------------------------|
| Release time   |                                          | Berger and Milkman (2012), Yoo et al. (2019), etc |
| $rel_t$        | Time when article is pushed, working day or not |                                             |
| Release position |                                         |                                             |
| $rel_p$        | The place of the article in a push, No. 1 or No. 2 |                                             |
Table 2: Correlation and descriptive statistics

| Variable    | Mean   | SD    | (1)  | (2)  | (3)  | (4)  | (5)  | (6)  | (7)  | (8)  | (9)  | (10) | (11) | (12) | (13) | (14) |
|-------------|--------|-------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1) share_total | 297.19 | 732.8 | 1.0  |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 2) share_net  | 109.27 | 316.8 | 0.94 | 1.0  |      |      |      |      |      |      |      |      |      |      |      |      |
| 3) share_user | 187.92 | 447.4 | 0.97 | 0.83 | 1.0  |      |      |      |      |      |      |      |      |      |      |      |
| 4) title_type | 2.20   | 1.0   | −0.04| −0.07| −0.01| 1.0  |      |      |      |      |      |      |      |      |      |      |
| 5) img_n      | 20.91  | 17.7  | 0.10 | 0.05 | 0.11 | 0.02 | 1.0  |      |      |      |      |      |      |      |      |      |
| 6) favor_n    | 68.09  | 148.57| 0.47 | 0.39 | 0.49 | 0.04 | 0.07 | 1.0  |      |      |      |      |      |      |      |      |
| 7) emo_tone   | 1.89   | 0.77  | −0.00| 0.01 | −0.02| −0.08| −0.20|
|              |        |       |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| 8) wx_ce      | 0.62   | 0.48  | 0.12 | 0.11 | 0.12 | 0.05 | 0.12 | 0.03 | 0.03 | 1.0  |      |      |      |      |      |      |
| 9) fol_n      | 578,476.1 | 407,033.1 | 0.26 | 0.22 | 0.27 | 0.05 | 0.21 | 0.32 | 0.03 | 0.27 | 1.0  |      |      |      |      |      |
| 10) read_n    | 12,322.36 | 15,968.41 | 0.65 | 0.60 | 0.63 | 0.02 | 0.26 | 0.40 | −0.00 | 0.17 | 0.62 | 1.0  |      |      |      |      |
| 11) like_n    | 65.41  | 149.33| 0.44 | 0.45 | 0.40 | −0.02| 0.16 | 0.26 | −0.03 | 0.20 | 0.38 | 0.71 | 1.0  |      |      |      |
| 12) com_n     | 22.54  | 55.48 | 0.31 | 0.31 | 0.29 | −0.03| 0.15 | 0.17 | 0.04 | 0.12 | 0.34 | 0.55 | 0.63 | 1.0  |      |      |
| 13) rel_t     | 0.50   | 0.50  | 0.02 | 0.02 | 0.02 | −0.05| 0.05 | 0.09 | −0.03 | −0.06 | −0.03 | −0.02 | −0.02 | 1.0  |      |      |
| 14) rel_p     | 0.52   | 0.50  | 0.20 | 0.20 | 0.19 | −0.00| 0.03 | 0.16 | 0.01 | −0.06 | −0.10 | 0.30 | 0.17 | 0.21 | −0.01 | 1.0  |
5.2 Estimation results and hypothesis testing

We set the dependent variables as the total number of shares, the number of shares on Moments, and the number of shares with friends. STATA was used to obtain the regression results (Table 3).

Unexpectedly, many coefficients were significantly negative. On the central route, the results showed that title rhetoric decreased article sharing. In other words, the impact may be negative; thus, \( H1 \) is refused. This result contradicts some previous research (Benoit and Smythe 2003; Scaraboto et al. 2012; Fulgoni and Lipsman 2017); however, it is also consistent with other research (Scacco and Muddiman 2016; Beleslin et al. 2017; Zhang et al. 2020). We speculate that, due to fierce competition, title rhetoric has been abused, resulting in negative user emotions. The coefficient for \( \text{img}_n \) was positively significant at \( p < 0.01 \), implying that the number of images embedded in an article affects the number of people who share it, and the effect is negative. Thus, \( H2 \) is not supported. Some scholars point out there is not a linear relationship between the number of pictures and the effect (Singh et al. 2000; Chowdhury et al. 2011). We speculate that, although processing pictures consumes less energy than processing words, too many pictures will not play a positive role but will instead cause unnecessary consumption, resulting in negative effects. The coefficient for \( \text{favor}_n \) was positively significant at \( p < 0.001 \), suggesting that perceived usefulness is conducive to individual sharing, which is consistent with previous studies. Therefore, we find strong support for \( H3 \). The coefficient for \( \text{emo}_\text{tone} \) indicates that articles full of negative emotions are more likely to be shared on

| Table 3 Dependent variable definition details | Variable | \( \text{share}_{\text{total}} \) | \( \text{share}_{\text{net}} \) | \( \text{share}_{\text{user}} \) |
|---|---|---|---|---|
| \( \text{title}_\text{type} \) | 2 | \(-123.7764^{**}\) | \(-50.40173^*\) | \(-73.37467^{**}\) |
| | 3 | \(-74.20152\) | \(-50.33837^{**}\) | \(-23.86315\) |
| | 4 | \(-131.8046^*\) | \(-74.04375^{**}\) | \(-57.76082\) |
| \( \text{img}_n \) | \(-2.682816^{**}\) | \(-1.446396^{**}\) | \(-1.23642^{**}\) |
| \( \text{favor}_n \) | 1.379019^{***}\) | 0.4511185^{***}\) | 0.9279006^{***}\)
| \( \text{emo}_\text{tone} \) | 2 | 84.63191^{*}\) | 51.34063^{**}\) | 33.29128 |
| | 3 | 22.32799\) | 12.25615\) | 10.07184 |
| \( \text{wx}_{\text{ce}} \) | 132.3581^{***}\) | 50.16152^{**}\) | 82.19656^{***}\)
| \( \text{fol}_n \) | \(-0.0005847^{***}\) | \(-0.0002291^{***}\) | \(-0.0003557^{***}\)
| \( \text{read}_n \) | 0.0393542^{***}\) | 0.0145275^{***}\) | 0.0248267^{***}\)
| \( \text{like}_n \) | \(-0.4585679^{**}\) | 0.031907 \) | \(-0.4904748^{***}\)
| \( \text{com}_n \) | \(-0.3665095\) | \(-0.1988027\) | \(-0.1677068\)
| \( \text{rel}_p \) | \(-154.0925^{***}\) | \(-49.55322^{***}\) | \(-104.5393^{***}\)
| \( \text{rel}_t \) | 23.16627\) | 12.8938\) | 10.27247|
| \( \text{Adj R-squared} \) | 0.5296\) | 0.4459\) | 0.5298|
| \( \text{Prob} > F \) | 0.0000\) | 0.0000\) | 0.0000|

\(*p<0.05; **p<0.01; ***p<0.001\)

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Moments but not significantly more likely to be shared with friends. Thus, $H_4$ is partially supported. Previous studies implying that articles with negative emotions are more likely to be shared are mainly based on social media such as Twitter, which is similar to sharing on Moments.

The coefficient for $wx_{ce}$ showed that WOAs’ authority, that is, whether an account is certified, significantly affects people’s sharing-behavior decisions. Articles published by certified accounts are more likely to be shared, which is consistent with previous research (Ha and Ahn 2011; Liu et al. 2012; Lu et al. 2021). Thus, $H_5$ is supported. Surprisingly, the coefficient for $fol_n$ was significantly negative. This means that the number of followers may hinder users from sharing, to some extent. Thus, $H_6$ is refused. This is different from some previous research (Luarn et al. 2014) on short texts like those on Twitter and Weibo, but one explanation might be that network redundancy is positively associated with information redundancy, which in turn decreases the probability of being shared (Liang and Fu 2016). We believe that information published by accounts with many followers is easily seen by users’ friends. This might be why the number of fans has a negative impact on sharing. The coefficients for $read_n$, $like_n$, and $com_n$, indicate that the number times articles are read has a positive effect on sharing, while the number of likes has a negative impact on sharing with friends. It is evident that the more people read, the more they potentially share. There are some differences between likes and sharing (Lahuerta-Otero et al. 2018), and content with a large number of likes may mean that many people have read it, which might decrease the likelihood of sharing. Therefore, $H_7$ is partially supported.

### 5.3 The Relative Importance of Determinants

Dominance analysis was used to understand the relative importance of the significant factors. This method aims to determine the contribution of different explanatory variables to the coefficient of determination, $R^2$ in linear regression. The explanatory variables are shown in order of importance in Table 4.

| Variable  | $share_{total}$ | $share_{net}$ | $share_{user}$ |
|-----------|-----------------|---------------|----------------|
|           | Dominance Stat  | Ranking       | Dominance Stat | Ranking | Dominance Stat | Ranking |
| $title_{type}$ | 0.0048          | 6             | 0.0078         | 5       | 0.0040         | 7       |
| $img_{n}$   | 0.0043          | 7             | 0.0045         | 7       | 0.0045         | 6       |
| $favor_{n}$ | 0.1200          | 2             | 0.0877         | 2       | 0.1359         | 2       |
| $emo_{tone}$ | 0.0040          | 8             | 0.0086         | 4       | –              | –       |
| $wx_{ce}$   | 0.0059          | 5             | 0.0063         | 6       | 0.0056         | 5       |
| $fol_{n}$   | 0.0366          | 4             | 0.0355         | 3       | 0.0362         | 4       |
| $read_{n}$  | 0.2753          | 1             | 0.2968         | 1       | 0.2750         | 1       |
| $like_{n}$  | 0.0760          | 3             | –             | –       | 0.0641         | 3       |
The number of times an article is read and the number of people who collect articles are the two most important factors. The number of likes plays a substantial role in sharing with friends, whereas articles’ emotional tone is more important in sharing on Moments. Authentication or not, the number of images, the type of title, and their impacts on users’ sharing-behavior decisions rank at the end.

6 Discussion and Conclusions

6.1 Key Findings

This study aimed to answer the three research questions raised in the Introduction (i.e., What are the determinants of users’ article-sharing behavior decisions on social media? Which factors are the most influential? Is there difference in the factors affecting users’ sharing-behavior decisions in different channels?).

For RQ1: The regression results indicate the determinants influencing users’ article-sharing behavior decisions on social media include the number of times an article was read, the number of likes, the number of the account’s followers, pictures contained in the article, people who collected the articles (i.e., perceived usefulness), author certification, emotional tone, and the title rhetoric. Among these determinants, the number of times read, number of people who collected the article, and author certification have positive impacts on users’ article-sharing behavior decisions. Negative sentiment will promote users to share articles. Rhetorical titles and other factors have a negative effect on users’ sharing-behavior decisions.

For RQ2: The number of times articles were read and how often they were collected are the two most important determinants for article-sharing behavior decisions. That is, the more people read and find a given article useful, the more it is shared.

For RQ3: There are some differences in the factors affecting users’ sharing-behavior decision in different channels. Exaggerated and incomplete titles negatively affect users’ willingness to share articles to online communities, but they do not influence users’ sharing with friends. Negative emotional articles are more likely to be shared to online communities, but emotional tone has no significant effect on users’ sharing with friends. Furthermore, the number of likes has a negative impact on sharing with friends but has no effect on sharing with online communities. Variations in determinants cause some differences in the order of influencing factors’ importance in different channels, but the difference is relatively small.

6.2 Theoretical Contribution

Our study offers several contributions to social media research. First, it contributes to the information diffusion literature and provides insights regarding what factors induce individuals to share articles on social media platforms. According to previous studies, there is plentiful research examining users’ sharing-behavior decisions, but it often focuses on short texts (Eckler and Bolls 2011; Berger and Milkman 2012;
Although short online texts (e.g., tweets and micro-blogs) are popular, reading long texts online (e.g., e-magazines and e-newspapers) is gradually becoming more common for its convenience and lack of cost (Tarkiainen et al. 2009; Graham and Greenhill 2013). Among long texts, only sharing behavior regarding online news has been studied (Lee and Ma 2012; Su et al. 2019; Apuke et al. 2020); less attention has been paid to the fact that long texts usually convey richer meaning (Deng et al. 2021). To the best of our knowledge, this study is one of the first to directly apply the ELM to examine sharing-behavior decisions regarding general long texts on social media. Our model proves to be a viable theoretical foundation based on empirical results. We believe that our work can provide inspiration and reference for future research examining the sharing of long texts.

Our research also suggests that a comprehensive investigation of determinants of users’ article-sharing behavior decisions is necessary and important. After comparing many models, we chose the ELM, which is frequently used in information-related decision-making processes (Sussman and Siegal 2003; Ha and Ahn 2011; Shi et al. 2018; Aghakhani et al. 2020; Thompson, et al. 2020). The overarching theoretical framework allows us to integrate various factors into the model and classify them into two influence routes (Petty and Cacioppo 1986).

Our results suggest that positive influences in short texts may play negative roles in long texts. Article-title rhetoric, the number of images, and the number of followers are significantly negatively correlated with users’ article sharing in long texts, but may have positive impacts in short texts (Suh et al. 2010; Park and Kaye 2019; Ordenes et al. 2019; Peng et al. 2018). This is an interesting finding and reveals the difference in sharing factors between long and short texts.

Third, we examined the factors’ relative importance and found that informational social influence and perceived usefulness have the largest influence on individual sharing-behavior decisions on social media platforms. This extends previous research on text sharing (Berger and Milkman 2012; Shi et al. 2018). Meanwhile, few previous studies have compared different channels of sharing. Some prior research studied online content’s impact on offline content (Tarkiainen et al. 2009; Graham and Greenhill 2013), but this study is one of the few to compare the factors that influence users sharing to different online channels. This aspect contributes to improving our understanding of users’ sharing-behavior decisions.

6.3 Practical Contribution

This study has several implications for practitioners. First, it can help account operators understand what motivates individuals to share online articles. With the exponential growth of online articles, achieving growth and enhancing user activity has become an inescapable challenge for every account operator. Companies often create online brand campaigns as an essential part of content marketing, in the hope that people will share the content with others to promote products and enhance influence power, but these campaigns’ success can vary widely. Our findings can be beneficial for marketers and account operators to better understand users.
Second, operators can employ the ELM’s central and peripheral routes to encourage individuals’ sharing-behavior decisions. The central route suggests that using too many images is not conductive to users’ article sharing. Article quality is important, especially providing users with useful content; for example, a film review might collate several classic films of the same genre. Using rhetoric such as hyperbole and rhetorical questions in headlines does not have a positive effect, but a negative tone has a positive effect on sharing to online communities. The peripheral route implies that account certification is important. Articles published by accounts with many followers may try not to track hot or have the first release at a hot time, which may reduce how often the articles are shared. When operators skillfully use the factors that promote sharing-behavior decision-making and avoid inhibitory factors, they can better understand users. This has practical significance for making best use of WeChat user behavior and interests, product marketing, hot event prediction, and so on.

Third, this study identifies the most critical points influencing users’ sharing-behavior decisions for practitioners. While many factors affect these decisions, practitioners’ focus should be on whether an article is interesting and useful to readers; the other factors are relatively less important. This study could also have implications for readers with significant social media use in the COVID-19 pandemic-influenced online society.

### 6.4 Limitations and Future Research

One limitation of this research is that our analysis is based on WOA data, which may raise issues of generalizability. Although WeChat is one of the most widely-used social media, the present findings may not directly extend to other social media platforms. For example, different from WeChat, which has a separate entry for reading articles, LinkedIn’s home page presents part of the articles directly, as well as the numbers of times read, likes, and comments. Thus, presenting part of the article and information about social influence may play a significantly positive role in article sharing. In addition, WOAs do not disclose certain information about their subscribers, to protect their privacy; therefore, the publisher’s and users’ identity, occupation, or even profile picture may play a role in article sharing. Thus, future research could expand our model to other social media platforms, such as LinkedIn and Facebook. And we hope to study users’ sharing behaviors by taking their occupation, culture, hobbies and other characteristics as influencing factors.

Second, although this study found that using too many images is not conducive to article sharing, we did not investigate how many images constitute a reasonable range or whether different types of images affect sharing behavior. Therefore, in future studies, we hope to further explore the relationship between images and article-sharing behavior.

Third, due to the closed nature of WeChat, our analysis is based on limited data. This restricts our ability to measure individual factors such as users’ personality or propensity to share; thus, we did not examine the effect of individual personality in the current study. In future studies, we plan to launch questionnaire surveys with
some followers so that individual factors can be included and more convincing and rich conclusions can be obtained.

Fourth, valid users were restricted to Chinese-language users in this research. However, given the global user base of social media, future research should also examine how cultural characteristics may affect users’ article-sharing behavior decisions.

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