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Effects of Platform and Content Attributes on Information Dissemination on We Media: A Case Study on WeChat Platform

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Abstract: The emergence of the WeChat has brought some new changes to people's ways of life and reading. Thanks to the WeChat Public Platform, many people from all walks of life have become We Media operators, creating their own brands and products. In a case study of WeChat Public Platform, this paper uses NLPIR, a tool for Chinese word segmentation, and SPSS, a data analysis software, to conduct an analysis of actual data captured by Web Spider about WeChat posts and the platform itself, exploring the effects of post content and platform attributes on users' reading and dissemination behaviors. Our regression analysis found that some content attributes, including parts of speech like adverb, punctuation marks such as question mark, and headline length and position, as well as platform attributes, such as the platform seniority, have significant impacts on page views; the genres of advertisement, joke and warning, among other content attributes, and follower count as a platform attribute, have a very significant effect on the dissemination index. This paper is helpful for operators to gain a better understanding of factors influencing the spread of information published by WeChat Official Accounts and providing valuable revelations on achieving fast and efficient dissemination of posts.

Keywords: Information dissemination, We Media, WeChat Public Platform, SNS Community.

1. INTRODUCTION

The development of IT application provides a brand new way of interpersonal communication and information publishing and sharing. Socialized We Media platforms like WeChat Official Accounts have received wide attention recently. Their strong abilities in information dissemination mainly owe to the fact that their users undertake the function of producing and spreading information while consuming information. The concept of We Media has been well-known as early as the era of individual blogs and websites booming. With the rise of Weibo and WeChat in recent years, We Media have regained popularity.

With the explosive growth of WeChat, an increasing number of social elites have applied for a WeChat Official Account. For the general public, they are free to release and spread information on We Media platforms. Such a freedom indicates limitless, explosive propagation of information. The unrestrained growth of We Media and the drastically growing passion of their followers produce inestimable momentum toward information dissemination on We Media in the future.

Nonetheless, not all We Media content are able to attract widespread attention and dissemination. Only a small number of We Media operators have managed to attract a large following, as information from operators often needs to reach average users through retransmission instead of direct transmission[1] [2]. The dissemination of information from WeChat Large V and well-known WeChat Official Accounts depends on celebrity influence and the quality of information itself. Hence, the study of content indexes will be beneficial for disseminating and spreading articles posted by WeChat Official Accounts, retaining the size and loyalty of the accounts' audience. In a study on user behaviors in the process of information dissemination, Jing et al. looked into WeChat information dissemination, analyzed problems that the expansion of WeChat may bring, and as a result proposed risk avoiding strategies for WeChat information dissemination [3]. In a study on factors affecting We Media

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information dissemination in SNS communities, Mathioudakis et al. conducted tracking and a predicative analysis by defining possible hot topics involving certain keywords [4]. Through an analysis of retweets and mentions of Twitter users' tweets, Cha et al. discovered that the more retweets, the more valuable the tweet is [5]. Most previous studies on factors affecting information dissemination used repost and bookmark counts or comment count as dependent variables. Moreover, most scholars focused their studies on the patterns of information dissemination on topic-centered comprehensive community-based We Media and "weakly bonded" fellowship-centered We Media based on SNS communities. Few of them studied information dissemination on "strongly bonded" or "weakly bonded" fellowship-centered We Media (WeChat Official Accounts).

In a case study on information dissemination on WeChat Official Account based on strongly or weakly bonded fellowship, this paper explores the effects of post content and platform attributes on user reading and dissemination behaviors, using the dissemination index as a measure of overall dissemination efficiency of posts. In the meantime, the analysis and study of content indexes will be beneficial for the dissemination and spread of WeChat Official Account posts, partly because it offer certain operation advices for WeChat Official Account operators, partly because it provides users with more reading experience catering to their reading habits.

2. STUDY ON RESEARCH MODEL AND INFLUENCING FACTORS

Based on literature review and theoretical study, the authors conducted comprehensive macroscopic and microscopic studies on factors affecting information dissemination on the WeChat Public Platform, centering around the forms and characteristics of information dissemination on WeChat. In this paper, factors affecting information dissemination are categorized into two types: content attributes and platform attributes. And there are two dependent variables: page views and the dissemination index. The research model is shown in Figure 1.

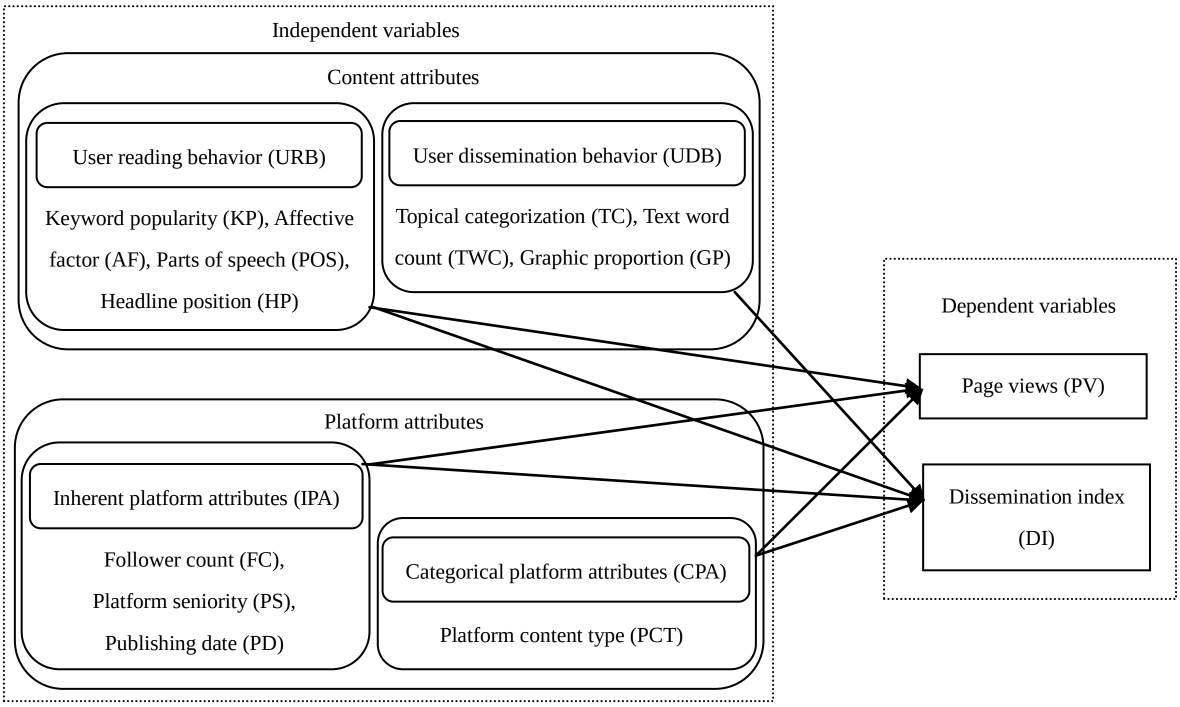

Figure 1. Research model

2.1 Content attributes

2.1.1 Factors affecting user reading behavior

• Keyword popularity. Keywords are words or phrases that users enter in the search bar when using a search engine, which can summarize to the largest extent the information content they are searching for. Keyword popularity affects user reading behavior to some degree [6].

• Affective factors. As a precursor of users' psychological inclination, affection can directly affect their decision making, i.e., whether users read or spread and share a post. Affective factors can affect users' attitude towards information acceptance [7].

• Parts of speech. Proper use of syntactic devices like ellipsis and function words can make a news headline more attractive [8]. Hence, a part of speech in a headline which is distinctively expressive can make the headline more appealing, and thus increase the probability of click-and-view by users.

• Headline length and position. The headline is information visible to users at first glance, whose length and position has important impacts on information reading. Yu maintained that headline position is vital and found that the average word count of headlines is 16.73[9]. As a WeChat Official Account can post only one message each day which may contain 1 to 8 posts, post position will also affect user reading experience.

2.1.2 Factors affecting user dissemination behavior

• Content genre. Content genre represents the overall style of posts. Targeting different user bases and pushing posts of their favorite genre to them is more likely to be well-received by them.

• Text word count. According to operators' past experience, a lengthy text burdens users with a heavy reading load, making it hard for them to attentively read through the text, let alone share and spread it, while a too short text may be empty of matter, some expressions in which may be unable to touch users, even impeding information dissemination. Hence, this paper uses the word count of text as one of the factors affecting information dissemination.

• Graphic proportion. The advent of the Era of Fragmentation has led to less time for people to spend on reading lengthy text, hence the combination of image and text can lighten their reading load and save their time spent on knowledge acquisition. In a study on Microblog, Yuan discovered that, although text is important, blogs with a combination of text and image usually attract more reposts [11]. The combination of text and image has become the mainstream of posts, but the specific ratios of text to image remain an area to be explored. Hence, this paper splits a post into text and image, and uses graphic proportion as an influencing factor.

2.2 Platform attributes

2.2.1 Inherent platform attributes

• Follower count. The more followers a user have, the more easily the information published by him/her will be followed and reposted [12]. The number of followers will most probably affect information dissemination on WeChat Public Platform, therefore this paper uses follower count as one of the influence factors.

• Platform seniority. In a study on user seniority on the Twitter platform, Suh et al. considered users whose accounts are over one year old as senior users, and came to a conclusion that the information released by a senior user can be more easily spread than that published by a new user[12]. We believe that the earlier a company was founded, the better established it will be; its information releases are thus more authoritative and reliable, and users will be more willing to share and repost them.

• Publishing date. When users go online depends on their daily schedule. Some scholars' study has shown that the publishing time has an impact on subsequent dissemination of a post. In their study, however, the publishing time is specified as a certain period of time of the day [13] [14]. As each WeChat Official Account generally pushes posts at a fixed time of the day, the author believes that the impact on information dissemination may vary with the publishing day due to users' work and preferences.

2.2.2 Categorical platform attributes

• Platform content type. Users within the same community with shared interests and hobbies are more willing to share on their common topics [15]. A wide variety of content is available on the WeChat Public Platform, and articles of differing content types are posted to different user bases. Zhang et al. made an analysis and comparison of repost frequencies of different content on Microblog and discovered that entertaining Microblog posts are most frequently reposted [16]. We are of the opinion that differences in content have a direct impact on information dissemination.

3. DATA CAPTURE AND PROCESSING

3.1 Data capture

This paper sampled WeChat Official Account posts captured by the website of XIGUA WeChat Official Account Assistant. The XIGUA WeChat Official Account Assistant is a content recommendation engine based on data mining, offering specialized content search and recommendation services for WeChat operators. It gathers data and information from a large number of WeChat Official Accounts and filters and sorts out breaking posts, hot posts, and self-created works published by WeChat Official Accounts.

This paper picks three columns, namely Affection and Self-Help, Automobiles, and Information from hot content rankings. To distinguish the effects of different factors on information dissemination, we chose WeChat official accounts from each category with follower counts in three different orders of magnitude, i.e., in the millions, the 100-thousands, and the 10-thousands, with the difference between two adjacent levels being a factor of 6-10. And in terms of platform seniority, we picked the accounts of companies which were founded a year apart. To ensure sufficient data, this paper gathered a total of 980 pieces of data, about 100 pieces of post information from each of the nine accounts under three categories, The raw data comprise 7 datasets, namely account type, the dissemination index, publishing time, headline, page views, like count, and founding time.

3.2 Data processing

The dissemination index is calculated with big data mining technology. Results are yielded by calculating weighted average page views, average like count, and publishing time of the posts of WeChat Official Accounts, and some corresponding coefficients. Good posts incur far more page views than ordinary posts. A breaking post would attract a readership far larger than the follower count. Hence, the ratio of page views to follower count can avert the impact of the follower base on viewing statistics. Other indexes like count are treated in the same way. The dissemination index is calculated by the definition and standardization of indexes and index weighting.

Table 1. Definition of indexes

Index	Definition
Follower count of a WeChat Public Account (FC)	Count of active followers of a Official Account post
Average page views (APV)	Average page views of a post in 24h
Average page views of similar posts (APS)	Average page views of other Official Accounts' posts in 24h
Average like count of similar posts (ALS)	Average like count of other Official Accounts' posts in 24h
Page views (PV)	page views in 24h
Like count (LC)	Count of likes received by a post in 24h

Table 2. Index standardization

Index	Standardization formula
Ratio of page views to follower count (R)	R= 1-1/(1+ PV/ FC)
Average Ratio of page views to follower count	R’= 1-1/(1+ PV/ APV)
Ratio of like count to follower count (L)	L= 1-1/(1+ LC/ FC)
Ratio of page views to average page views of similar posts	RP= 1-1/(1+ PV/ APS)
Ratio of like count to average like count of similar posts	LP= 1-1/(1+ LC/ ALS)

Weight varies from index to index. Dynamic adaptation is repeatedly conducted with the machine learning model of logistic regression to get the most appropriate proportioning. Below is the calculation formula of the dissemination index (XPR)

$$XPR= R * W_1 + R' * W_2 + L * W_3 + RP * W_4 + LP * W_5$$

In this formula, $W_{1…N}$ refer to weights of different indexes, the values of which are:

$$W_1= 0.3, W_2= 0.1, W_3= 0.2, W_4= 0.15, W_5= 0.25$$

We preprocessed all collected data for regression analysis. The process is shown in Table 3.

Table 3. Data preprocessing

Influencing factor			Method of processing
Content attributes	URB	KP	NLPIR is used to segment post headlines to extract keywords. For instance, the segmentation of "Only this mountain dares to compete with the Palace Museum in the beauty of snow scene!" produces two keywords: "the Palace Museum" and "snow scene". The "search index" function of Baidu Index is used to quantify the popularity of keywords in 7 days from the publishing day and calculate the average value.
		AF	NLPIR is used to divide affections into three categories: positive, negative, and neutral.
		POS	Headlines are divided by NLPIR into 7 parts of speech, namely adverb, noun, classifier, adjective, verb, common phrase, and idiom.
		HL	Headlines are divided by length into short (word count≤16) and long (word count>16).
		HP	Statistics of headline position sequences
	UDB	TC	Post text content is categorized by topic by NLPIR and the categorization has been adjusted repeatedly include affection, self-help, advertisement, life, art, disabuse, test, health, joke, entertainment, society, case story, warning, recommendation, and zodiac in total 15.
		TWC	Word counts of post texts
		GP	Posts are categorized by the graphic proportion into three types: small, medium, and large.
Platform attributes	IPA	FC	Follower counts have been displayed directly when data are captured by the Xigua Official Account Assistant and therefore need no processing.
		PS	An examination of the founding time of WeChat Official Accounts revealed that they were all founded by 2012 ~ 2016; the value of platform seniority is 1 for 2012~ 2014 and 0 for 2015 ~ 2016.
		PD	As each account generally posts its articles at a fixed time of the day, this paper converted the publishing date to the day of the week.
	CPA	PCT	This paper captures three types of posts, namely affection, automobile, and information, marked as types 1, 2, and 3 respectively.

In the table above, the main functions of the NLPIR segmentation tool include Chinese segmentation, parts of speech marking, name entity recognition and keyword extraction. This paper used NLPIR functions for data processing such as post headline segmentation, keyword listing, affection categorization, part of speech categorization, text topical categorization. Baidu Index is a data sharing platform based on a wealth of data about Baidu users' behaviors. Based on data about Internet users' searches on Baidu, and with keywords as object of statistics, it conducts scientific analyses and calculates the weighted sum of search frequencies of a keyword in Baidu webpage search [17].

What's more, in view of the very significant gaps between different official account posts in page views, ranging from a few dozens to 1 million, we apply a log transformation of page views to reduce data gaps and facilitate subsequent presentation of data analysis results. The dissemination index was also logarithmically processed.

4. DATA ANALYSIS

Based on the study and processing as described above, we used the SPSS data analysis software to conduct a multiple linear regression analysis of varying indexes affecting dependent variables and extracts significant influencing factors.

4.1 Significance analysis of factors affecting user reading

4.1.1 Significance analysis of content attributes

Parts of speech and punctuation marks, as well as AF, HL and HP, and KP are incorporated into the linear regression model as dependent variables. Nonetheless, not all variables are always significantly correlated with and linearly dependent on PV. The results of a SPSS regression analysis of data are shown in Table 4. This paper used stepwise selection (standard: entry probability≤0.05, removal probability≥0.1) to sort out seven highly significant characteristic variables, namely HL, exclamation mark, HP, classifier (p=.000), adjective (p=.002), question mark and adverb (p=.003). Among them, HL, exclamation mark and HP are negatively correlated with Log PV, meaning that the more classifiers, adjectives, adverbs and questions, the more PV. Our analysis of collinear statistic index discovered that the tolerance and VIF of every variable are both close to 1, hence correlation among influencing factors is weak, which has less effect on coefficients in the regression equation and less significant effect on the results.

Table 4. Significance analysis of linear regression between content attribute variables and Log PV

Model	Non-standardized coefficient	t	Sig.	Tolerance	VIF
(Constant)	5.003	77.128	.000		
HL	-.037	-14.130	.000	.864	1.157
Exclamation mark	-.189	-7.212	.000	.908	1.101
HP	-.040	-4.420	.000	.976	1.024
Classifier	.215	3.874	.000	.951	1.051
Adjective	.103	3.173	.002	.985	1.015
Question mark	.075	2.985	.003	.984	1.017
Adverb	.068	2.961	.003	.958	1.004

4.1.2 Significance analysis of platform attributes

We incorporated FC, PS, PD and PCT into the linear regression equation for analysis, treating Log PV as an independent variable. Table 5 shows the linear regression between platform attribute variables and Log PV. Stepwise selection of linear regression eliminated non-significant PD and sorted out three most significant characteristic variables, namely FC, PCT (p=.000), PS (p=.012). Among them, PCT is negatively correlated with PV. The content types of affection and self-help, automobiles, and information are marked as 1, 2, and 3 respectively, indicating that the closer of content to the genre of affection and self-help, the more views a post will incur. By contrast, FC and PS are positively correlated with PV, demonstrating that the more FC has and the higher the PS is, the more views a post will incur. Our analysis of collinear statistic index discovered that the tolerance and VIF of every variable are both close to 1, hence correlation among influencing factors is weak, which has less effect on coefficients in the regression equation and less significant effect on the results.

Table 5. Significance analysis of linear regression between platform attribute variables and Log PV

Model	Non-standardized coefficient	t	Sig.	Tolerance	VIF
(Constant)	.202	1.847	.065		
Log FC	.753	42.043	.000	.976	1.101
PCT	-.025	-5.961	.000	.984	1.037
PS	.079	2.527	.012	.968	1.056

4.2 Analysis of the significance of factors affecting user dissemination

4.2.1 Significance analysis of content attributes

Fifteen categorized post topics and TWC, GP, Log PV, and attributes of URB are incorporated into the regression equation model as independent variables. Table 6 shows the linear regression between content attribute variables and Log DI. Stepwise selection of linear regression eliminated non-significant variables and sorted out the remaining nine significant characteristic variables, namely Log PV, advertisement, warning, HL, HP (p=0.00), zodiac (p=.002), exclamation mark (p=.003), joke (p=.018), and noun (p=.027). Among them, HP, noun, and advertisement are negatively correlated with dissemination index, showing that the more advertisements a post contains, the lower the dissemination index of the post; the more backward the HP and the more nouns the post contains, the lower the dissemination index will be. By contrast, Log PV, warning, joke, zodiac, exclamation mark, and HP are positively correlated with Log PV, indicating that the more PV, the higher DI; and the closer of post content to warning, joke, and zodiac, the easier the post will be spread by users, i.e., the higher DI; the longer the headline and the more exclamation marks in the post, the higher DI. Our analysis of collinear statistic index discovered that the tolerance and VIF of every variable are both close to 1, hence correlation among influencing factors is weak, which has less effect on coefficients in the regression equation and less significant effect on the results.

Table 6. Significance analysis of linear regression between content attribute variables and Log DI

Model	Non-standardized coefficient	t	Sig.	Tolerance	VIF
(Constant)	1.433	77.488	.000		
Log PV	.054	12.165	.000	.958	1.044
HL	.004	5.955	.000	.409	2.445
HP	-.007	-4.666	.000	.918	1.089
Exclamation mark	.013	2.979	.003	.806	1.240
Noun	-.004	-2.215	.027	.470	2.128
Zodiac	.047	3.127	.002	.853	1.173
Advertisement	-.077	-5.930	.000	.959	1.043
Warning	.048	3.886	.000	.993	1.007
Joke	.048	2.374	.018	.991	1.009

4.2.2 Significance analysis of platform attributes

We incorporated PS, Log FC, PD and PCT into the linear regression equation for analysis, treating Log DI as an independent variable. Table 7 shows the linear regression analysis of platform attribute variables and Log DI. Unlike the analysis results of factors affecting PV, PS and PCT are no longer significant factors affecting dependent variables, among which, the influencing factor of PCT is no longer significant due to some difference between platform type and post type. In the table below, only Log FC (p=.000) is the significant factor and positively correlated with the dissemination index, meaning that the more followers the platform has, the higher the dissemination index. As only the variable follower count is significant, both of the tolerance and VIF are 1, hence there is no collinear characteristic and the regression effect of the equation is good.

Table 7. Significance analysis of linear regression between content attribute variables and Log DI

Model	Non-standardized coefficient	t	Sig.	Tolerance	VIF
(Constant)	1.568	73.592	.000		
Log FC	.017	4.301	.000	1.000	1.000

5. DISCUSSION

5.1 Significance analysis of factors affecting user reading

• Content attributes. As shown by the significance analysis results of content attributes, the seven variables of classifier, adverb, adjective, exclamation mark, question mark, headline length, and headline position are significant. Among them, classifier, adverb, adjective, and question mark are positively correlated significant variables, probably because the information signals expressed by these influencing factors can easily evoke users' empathy or curiosity. Exclamation mark, headline length, and headline position are negatively correlated significant variables, because if the values of the three influencing factors are too high, it may bring a heavy reading load on users or provoke their resistance to reading. For example, too many exclamation marks, however, may perceive overly strong warning and feel stressed to users while reading. It therefore has a negative effect on the growth of page views. As a feature of the current Era of Fragmentation, users would rather spend less time in reading more valuable content, as excessively long headlines may increase their reading load and consumption of mental energy. Hence, headline length is negatively correlated with page views. Due to the top-down reading, habit among most users, the more forward the headline is, the easier it attracts users' attention; hence the more forward a post's headline is the more views the post will attract.

• Platform attributes. As can be seen from the significance analysis results of platform attributes, follower count, platform seniority, and Platform content type are all significant attribute variables, while the publish date is non-significant. The reason why follower count and platform seniority are positively correlated with page views is obvious: the more followers an account has, the more people will click and read the post, e.g., page views will rise with the increase of followers. And more often than not, the higher the platform seniority, the more faithful and authoritative the information published by the platform, hence the more probable users will click and read the information. Platform content type is negatively correlated with page views. As affection-themed WeChat Official Accounts have more followers, and affection-conscious users are largely female who are more keen on reading information released by such accounts, hence their posts incurs more views. The publishing date and page views are not linearly related probably for two reasons: first, users have become accustomed to the fact that new articles are posted every day. It is likely that a user visits an account every day and visits another account only occasionally, so his/her frequency of visiting each account may basically remain unchanged. Therefore, the publishing date has no significant effect on page views; second, the small sample size may conceal some weak effects.

5.2 Significance analysis of factors affecting user dissemination

• Content attributes. According to the significance analysis results of content attributes, the four variables of page views, warning, advertisement, and joke are significant. The three variables of page views, warning, and joke are positively correlated with the dissemination index. The impact of page views on the dissemination index is attributable to users' conformist mentality or vanity. The page views of each post are shown at the bottom left corner. When a post incurs many page views, users will often consider it a popular post which is reliable and well-received, and are more willing to share it. The word count of text and image count are not significantly correlated with the dissemination index. The reasons might be : First, if users are interested in the content, the probability of them minding word and image counts will decrease; however, when the quality of content is poor, even if the layout is good with reader-friendly word and image counts, users will be unwilling to share and repost it. Second, in data sampling, this paper chooses posts similar in layout with little difference in word and image counts, thus having little effect on the dissemination index.

• Platform attributes. As can be seen from the significance analysis results of platform attributes, only follower count has significant effect on the dissemination index. The reason is that the more followers the platform has, the greater the chance of the post being viewed and hence the greater probability of being shared and spread. Platform seniority, platform content type, and publishing date are all non-significant correlated with the dissemination index. The effect of platform seniority may attribute to the fact that, in our times of constant substitution and overlap of information, the same article may be posted by different WeChat Official Accounts, therefore users may be more concerned about the post itself rather than accounts' platform seniority. The impact of platform content type may be attributable to the fact that, when deciding whether to spread a post, users may often lay more emphasis on its content rather than that of the account itself.

6. CONCLUSION AND OUTLOOK

6.1 Conclusion

Our paper focuses on factors affecting information dissemination on We Media platforms based on WeChat Official Accounts. We systematically categorized factors affecting information dissemination, and conducted a study of these influencing factors based on a linear regression model. Through observing the significant characteristics of variables, we extracted factors effectively affecting information dissemination. Our classified study of articles posted by WeChat Official Accounts leads to the following findings. First, follower count is an important index which affects user reading and dissemination. Therefore, attracting more followers is a matter of vital concern to operators. Second, an eye-catching headline matters. Operators need to place stress on the parts of speech in a headline and other headline attributes. Third, for article posting, on the condition that the interests and hobbies of users are met, moderately posting entertaining and joking articles can promote the dissemination of posts. Nonetheless, it is advisable not to post advertorials, which is counterproductive.

6.2 Revelations for managers

In the current Era of Fragmentation amid the rapid development of the Internet, We Media users have a stronger tendency to acquire the most valuable of content in the shortest possible time. For managers of WeChat Official Accounts, an appropriate headline will help attract the attention of users, prompting them to click and view the post and then repost and share it with others.

There are countless WeChat Official Accounts of various categories. The findings of this paper show that users prefer WeChat Official Accounts belonging to the genre of affection and self-help. Such accounts can accommodate more topic types, and their users are more likely to be female. For new operators of WeChat Official Accounts, therefore, targeting bigger user bases will be more helpful to increase the count of fans and the rapid propagation of their posts.

WeChat Official Accounts featuring the same content type may publish posts on distinct topics. When posting articles, operators first need to identify what type the user populations of senior public platforms are sensible or emotional. If users are receptive to various types of posts, operators can post some entertaining and joking articles which are easier to disseminate and spread; if opposite, it is desirable to post articles in line with the platform content type and avoid posting advertorials to achieve more effective dissemination.

6.3 Deficiencies and outlook

First of all, in the study on factors affecting user reading behavior, keyword popularity and the category of affection are both non-significant, contrary to our expectation. In the process of pre-processing data, we based the algorithm of keyword popularity on the comprehensive popularity index of Baidu Index. Since the WeChat Official Account platforms are mostly accessed by mobile devices, subsequent studies may use the mobile popularity index of Baidu Index to effectively avert the impact of PC-based popularity index.

Secondly, in the choice of WeChat Official Accounts, this paper focuses on the genres of affection and self-help, automobiles, and counseling. In future, more genres, e.g. funnies, sports and tourism, may be added for more detailed comparative studies to further explore whether the impact on information dissemination will change with the difference in genre.

Finally, in our study on factors affecting the dissemination index, we did not take content quality into consideration. So far academia have not yet had consensus on the definition of content quality. It is generally defined the perspectives of users or information. Studies on content quality are multi-dimensional. In later follow-up studies, it is advisable to conduct detailed, in-depth studies on the impact of content quality on the dissemination index.

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