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Factors Influencing Information Sharing among Users of Online Communities: A Meta-Analysis

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Abstract: When discussing the question of what influences information sharing among users of online communities and the extent to which it is strong, researchers have come up with different views, which has hindered the development of online community research. This study compares the empirical studies of previous scholars and systematically analyses their influencing factors and strengths with the help of meta-analysis. Twenty-seven Chinese and English literatures were collected and analyzed to identify and code 15 significant factors influencing information sharing among online community users, and to test for heterogeneity and publication bias. The study found that the influencing factors could be divided into 6 external factors and 9 internal factors in two categories. 7 moderately correlated factors and 8 weakly correlated factors were also derived based on correlation coefficients. Of these, technical effectiveness and control had the greatest impact on information sharing among users of online communities, followed by perceived usefulness and information quality. External factors were mainly concentrated in the moderately relevant category. Theoretical and practical implications for community operations and managers are discussed in light of these findings.

Keywords: Online community, Information sharing, Meta-analysis, Influence Factor

1. Introduction

The rapid development of Internet technology has brought about rapid economic and cultural development on different levels all over the world. Online communities, as information infrastructure and tools used to produce and distribute content [1], are playing an increasingly important role in the vast scope of social networks. As we can see, practices of sharing information via social networking services are pervasive and diverse [2], and online communities are increasingly moving away from the World Wide Web and toward a platform to facilitate information exchange between users [3]. So the act of sharing information makes online communities more active than those that receive information, which also brings benefits to Internet service providers, community builders, advertisers, and information seekers.

In recent years, there has been a growing interest in research on what exactly influences the information sharing behaviour of online community users. A number of empirical studies have been conducted to explore and empirically analyse these questions in depth. However, studies have shown that the factors and the degree of influence found in different studies that affect the information sharing behaviour of online community users vary, and the findings do not reach a good agreement. Some studies have found that reciprocity as an influencing factor is strongly associated with information sharing among online users [4], but some scholars have also found that reciprocity does not have a significant effect on information sharing [5]. Zhou, etc. argue that emotional support is not significant for information sharing among online users [6], while some scholars argue that emotions are significantly related to information sharing [7-8]. The divergent findings of previous scholars then make it somewhat of a hindrance to exploring general patterns and theoretical proposals on the factors that influence information sharing among online users.

Meta-analysis is a tool for systematic and comprehensive analysis of the results of different studies on the same issue. Meta-analysis allows researchers to arrive at conclusions that are more accurate and more credible than can be presented in any one primary study or in a non-quantitative, narrative review [9]. Using the meta-analysis method, firstly, it is possible to systematically explore the factors and motivations that influence information sharing among online users, refine the limitations of some of the thesis findings, and provide community managers and service providers with strategies and suggestions to stimulate the flow of information and increase the activity of online communities; secondly, it is possible to analyse the moderating variables that influence information sharing among online users as a way to explain variability in greater depth.

2. Review of Research

Researchers' studies on the influencing factors of information sharing among users of online communities have mostly used empirical methods to conduct analyses, mostly using theoretical models proposed by previous scholars and their extensions or selecting influencing factors from relevant qualitative papers to conduct validation survey experiments. The platforms selected for study include social chatting communities such as Facebook and Wechat [10-12]; micro-blogging communities such as Twitter and Sina Weibo [13-14]; knowledge-based communities such as Zhihu and Quora[15-16]; video sharing communities such as Youtube and Bilibili [17-18]; and vertical functional communities [19-22]. Researchers' choice of research subjects varies according to the platform and direction of the study. For example, in a social chat community like Wechat, users are more inclined to consider the quality of information and the atmosphere of information interaction when sharing information, which contributes to smooth acquaintance socialization or potential social behaviour [11,23]. In contrast, in online question and answer communities like Zhihu, users are more concerned with subjective norms, self-efficacy, rewards, and honors [15-16]. Throughout the vast majority of studies, users of online communities have been selected as respondents. There are also segmented personas such as travelers, video bloggers and programmers set for the direction of the study. College students and teenagers, as groups that are more likely to have focused access to questionnaires and are active in various online communities, are the main targets of research studies.

In addition, the theoretical underpinnings or the literature on models used by researchers largely determine which influences are used to design questionnaires, conduct surveys and draw conclusions. A review of the literature reveals that theoretical models focus on the Technology Acceptance Model (TAM) [24-25], and its extensions (UTAUT) [30,25]; Social Cognitive Theory (SCT) [5,26]; Expectancy Confirmation Theory [27]; Social Exchange Theory [26,28]; and Information Ecological Factor Theory [11,23,29]. Researchers usually use a combination of one or more theoretical models to identify the factors and motivations that influence online users' information sharing from the perspectives of sociology, psychology, media, and others, formulate hypotheses, collect data through questionnaires and interviews, and quantitatively analyse the relationships between the variables. In general, a large number of scholars have taken an interest in and conducted quantitative research on the factors influencing information sharing among online users. However, due to different research perspectives and methods, it is difficult to draw consistent conclusions from the numerous studies. Although some scholars have used meta-analysis to explore the problems in the Social Sciences Field, few studies have been able to encompass all aspects of the factors influencing information sharing among online community users and draw generalized conclusions. This paper therefore presents a systematic analysis of the influencing factors in the existing literature based on a meta-analytic approach, and draws relatively consistent conclusions about the factors that influence information sharing among users of online communities.

3. Research Design

3.1. Method

Meta-analysis can aggregate many studies that use heterogeneous methods and metrics into common effect size measures [31]. Therefore, we need to collect a comprehensive sample of literature to ensure the objectivity of the meta-analysis results and to try to eliminate potential bias. The steps in the study (Fig. 1) began with the collection of relevant literature based on the question posed and screening it according to the requirements of the meta-analytic approach, followed by coding of the literature, including information extraction and identification of single effects; data analysis based on meta-analytic tools, including specific effects and subgroup moderator variables; and finally, discussion of the results.

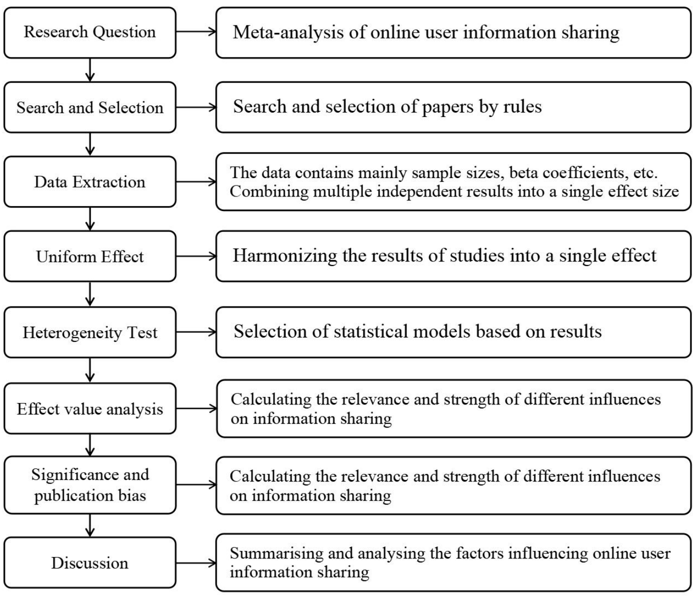

Figure 1: Steps in a meta-analysis study of online user information sharing.

3.2. Search and Selection

To ensure the scientific validity and reliability of this meta-analysis results, a comprehensive search of the literature involved in the study was conducted for this paper. The English paper search was conducted in web of science, Google Scholar on August 8, 2022. One of the searches was conducted in the advanced search function of web of science using the following search formula: ((((((((TS=(Online System)) OR TS=(System, Online)) OR TS=(Systems, Online)) OR TS=(On-Line Systems)) OR TS=(On Line Systems)) OR TS=(On-Line System)) OR TS=(System, On-Line)) OR TS=(Systems, On-Line)) AND ((TS=(information sharing)) OR TS=(information behavior))) AND TS=(influence factor). The Chinese paper search was then conducted in the

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advanced search function of CNKI using the corresponding Chinese translations as search terms, and supplementary searches were conducted in databases such as Baidu Scholar, Wanfang Database, and Weipu Database of Chinese sci-tech periodicals. The Chinese search terms included, but is not limited to, online communities; online communities; information sharing; information behaviour; influencing factors; information disclosure, etc.

The retrieved papers in English and Chinese were initially screened with the following criteria. Firstly, eligibility for inclusion was limited to papers with users of online communities and online communities as research subjects for empirical studies, excluding non-empirical research papers such as case studies, interviews, pure theories and literature reviews. Secondly, papers with empirical studies addressing the willingness and behaviour of research subjects to share information were selected. Thirdly, papers with similar or identical papers by the same scholars were excluded duplicate publications, especially journal papers and dissertation studies that are identical, and select one of them as a way to ensure that each is an independent study that does not contain the same sample. Lastly, papers must present data on sample size, correlation coefficients of influencing factors, etc. as effect values. All papers must be rigorously selected and, after excluding those that are not available, the selected papers are evaluated for cross-sectional research quality.

3.3. Paper Coding

This step of Paper coding requires the extraction of paper content and data, and the identification and classification of uniform effect indicators. The former is the extraction of information including basic information about the paper and the extraction of quantitative data necessary to enter the meta-analysis. The basic information of the paper includes the author, subject of the paper, date of publication, source of publication, online platform category, etc. The quantitative data extraction includes the sample size, correlation coefficient, etc. After extracting the relevant data, the effects with differences in different studies need to be categorized and named based on the context and definitions. The effect in the English paper were professionally translated, while the explanations and definitions of the effects in the text were retraced and analyzed, and finally unified with the Chinese effects.

4. Results

4.1. Sample Coding Results

As of August 8, 2022, 1437 English and 590 Chinese-related papers were obtained through various literature searches, respectively. According to the criteria designed in the research methodology, a total of 27 eligible papers were obtained after three rounds of rigorous screening to enter the meta-analysis process, including 15 papers in English and 12 papers in Chinese. The total number of eligible papers included 24 journal papers and 3 dissertations, spanning the period from 2010 to 2021. The selected completed papers were read carefully and assessed for risk of bias based on the Cochrane ROB tool in six main areas: selection bias, performance bias, detection bias, attrition bias, reporting bias, and other bias, resulting in a risk of bias graph (Fig. 2).

The meta-analysis was conducted with the help of Stata/SE software with the meta-analysis module and RevMan (Review Manager) 5.4 software. Since meta-analysis requires the same effect size to occur more than three times in different studies before it is included in the meta-analysis, 15 effects were sorted and generalized from 20 English papers and 11 Chinese papers to enter the meta-analysis, obtaining 101 effect values and 29,472 independent samples. Among them, the more discussed ones were reciprocity and reward which were mentioned 14 times in relation to online user information sharing; perceived usefulness was mentioned 11 times; emotional support was reported 10 times, etc. Table 2 shows the overall meta-analysis results between online user information sharing and the influencing factors. The papers screened across and the theories employed therein cover the subject areas of journalism and communication, library and intelligence, management and information technology.

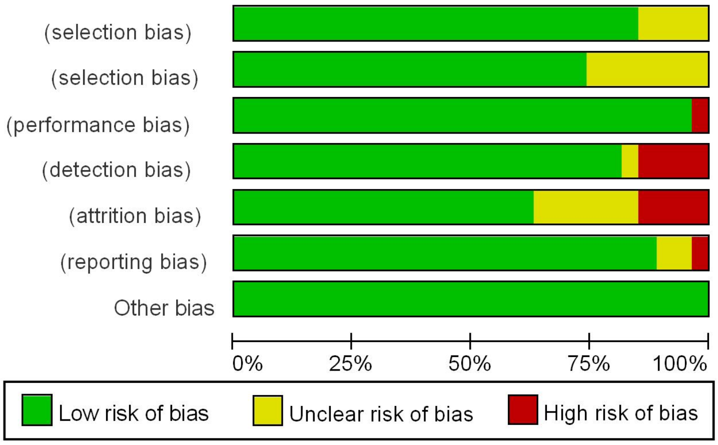

Figure 2: Risk of bias graph.

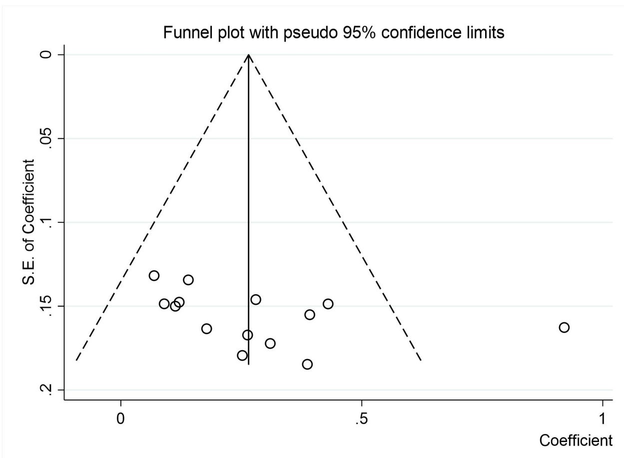

Figure 3: Funnel diagram: Reciprocity and Reward.

4.2. Heterogeneity Test

Before the formal meta-analysis, a selection of the applicable model for the meta-analysis needs to be made. Therefore, a test for heterogeneity in effect sizes is required. Currently, the main methods of testing for heterogeneity are the Q test and the I2 test. When the Q test is significant it indicates that the effect size is heterogeneous, if I2 is less than 75% it indicates that a fixed effects model is required, if it is greater than 75% it indicates that a random effects model is required. In order to select the appropriate model, the data were tested for heterogeneity and it was concluded that Q was greater than or even much greater than the degrees of freedom (df, df=k-1), and the p-values were all less than 0.05, showing significant, so indicating that heterogeneity existed between all effect sizes. From Table 2 it can be seen that I2 is greater than 75% in all cases, so a random effects model needs to be selected for meta-analysis.

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4.3. Publication Bias Test

A more controversial issue in the meta-analysis is that of the filing cabinet [32]. The quality and bias of the literature has previously been judged subjectively using Revman software based on Cochrane. A more scientific approach to testing publication bias is needed after entering the meta-analysis. For the direction of this paper and the characteristics of the sample, and reporting its high heterogeneity, Egger's Regression, Begg-Mazumdar rank correlation and funnel plots were chosen for publication bias analysis. A p-value greater than 0.05 from Egger's Regression and Begg-Mazumdar rank correlation indicated that there was no publication bias. The first option was to generate publication bias plots for each effect size in Stata software and to perform visual inspection. For example, the publication bias plot for the effect measure of reciprocity and reward (Figure 3) was found to be somewhat biased by visual inspection. Further quantitative tests were then conducted and the Egger's intercept for the effect measure of reciprocity and rewards is reported in Table 2 as 20.82106 ($p > 0.005$), thus concluding that there is no publication bias for this effect measure. The same approach was applied to each of the effect sizes and the relevant data are reported in Table 2. Combining multiple methods for publication bias testing revealed no publication bias for all effect sizes.

Table 2: Meta-analysis results of influencing factors of online user information sharing.

Effect	k	N	r	95% Conf.	Significance		Heterogeneity			Begg's test		Egger's test	
					Z	P	Q	p	I2 (%)	z	p	intercept	p
RR	14	3717	0.281	0.171,0.392	4.99	0.000	1041.58	***	98.80	1.92	0.055	20.82106	0.100
PU	11	3043	0.343	0.242,0.444	6.68	0.000	399.28	***	97.50	1.48	0.139	2.014941	0.841
ES	10	3167	0.245	0.128,0.362	4.11	0.000	1222.53	***	99.30	1.16	0.245	11.97785	0.001
ORI	10	3254	0.331	0.152,0.511	3.62	0.000	1481.51	***	99.40	1.16	0.245	-25.18182	0.180
SE	8	2070	0.324	0.187,0.460	4.65	0.000	405.52	***	98.30	0.49	0.621	19.65596	0.055
TEC	7	1646	0.450	0.296,0.604	5.73	0.000	278.3	***	97.80	-0.15	0.881	9.141605	0.461
IT	5	1712	0.307	0.136,0.478	3.53	0.000	307.36	***	98.70	1.47	0.142	18.13484	0.074
RB	5	1606	0.275	0.115,0.436	3.36	0.001	244.14	***	98.40	0.49	0.624	-4.337511	0.907
AD	6	1832	0.251	0.121,0.380	3.80	0.000	319.5	***	98.40	1.69	0.091	13.11927	0.002
PPR	5	1717	0.214	0.072,0.356	2.95	0.003	337.64	***	98.80	1.47	0.142	15.20484	0.027
IQ	5	1537	0.383	0.195,0.571	4.00	0.000	284.66	***	98.60	1.47	0.142	17.14965	0.117
SN	5	1064	0.331	0.048,0.615	2.29	0.022	812.2	***	99.50	1.47	0.142	16.23838	0.109
SM	4	1386	0.180	0.119,0.241	5.75	0.000	27.39	***	89.00	0.68	0.497	1.657698	0.915
NIT	3	800	0.282	0.217,0.347	8.53	0.000	8.27	**	75.80	0.52	0.602	6.086528	0.568
OF	3	921	0.113	0.010,0.216	2.15	0.032	70.66	***	97.20	1.57	0.117	19.03242	0.166

Note. RR = Reciprocal and reward; PU = Perceived usefulness; ES = Emotional support; ORI=Online relationship interaction; SE = Self-efficacy; TEC = Technical efficiency and control; IT = Institutional trust; RB = Reputation benefit; AD = Altruistic desire; PPR = Perceive privacy risks; IQ = Information quality; SN = Subjective norms; SM = Self-presentation and media exposure; NIT = Network information trust; OF = Online frequency. k = sample size ; N = The cumulative number of subjects for the k studies; r = D+L pooled correlation coefficient; 95% Conf.

= Lower limits and upper limits of the confidence interval; Z = The Z-value when the test of r=0(2-tail) ; P = The P-value when the test of r=0(2-tail) ;

4.4. Relationship Intensity Analysis

Cohen J. proposed a criterion for determining the strength of correlation by the correlation coefficient [33], with $0.00 \leq r \leq 0.09$ indicating essentially no correlation; $0.10 \leq r \leq 0.29$ indicating a weak correlation, $0.30 \leq r \leq 0.49$ indicating a moderate correlation, and $r > 0.50$ indicating a strong correlation. When the results are divided according to this criterion, it is obtained that all effect sizes are significantly correlated ($p<0.05$) with online community user information sharing as influencing factors. The influencing factors that have moderate correlation with online community user information sharing include Technical efficiency and control (r=0.450)； Information quality (r=0.383); Perceived usefulness (r=0.343); Online relationship interaction (r=0.331); Subjective norms (r=0.331); Self-efficacy (r=0.324); Institutional trust (r=0.307). The influencing factors that have weak correlation with online community user information sharing include Network information trust (r=0.282); Reciprocal and reward (r=0.281); Reputation benefit (r=0.275); Altruistic desire (r=0.251); Emotional support (r=0.245); Perceive privacy risks (r=0.214); Self-presentation and media exposure (r=0.180); Online frequency (r=0.113).

Table 3. The correlation relationship of the influencing factors.

Category	Influencing factor	
Medium correlation	External	Technical efficiency and control; Information quality; Online relationship interaction; ; Institutional trust
	Internal	Perceived usefulness; Subjective norms; Self-efficacy
Weak correlation	External	Network information trust; Perceive privacy risks
	Internal	Reciprocal and reward; Reputation benefit; Altruistic desire; Emotional support; Self-presentation and media exposure; Online frequency

5. Discussion

The information sharing behaviour of users in online communities can directly transform some users from viewers to information producers, which is especially important in UGC model communities. At the same time, the flow of information can facilitate the establishment and sustainability of online relationships and create a good information exchange atmosphere, which is crucial for the healthy development of online communities. When discussing the question of what influences the sharing of information among users of online communities and how strong the influence is, different or even opposing views have emerged in academia, which has hindered the development of online community research. Therefore, this paper compares the empirical studies of previous scholars and systematically analyses their influencing factors and strengths and weaknesses with the help of meta-analysis. Twenty-seven Chinese and English literature articles were collected and analyzed. By extracting experimental data, 15 significant factors affecting information sharing among users of online communities were identified and coded, and tested for heterogeneity and publication bias. The influencing factors included Method 1 and Method 2. The study found that the influencing factors could be divided into two categories: external factors and internal factors, of which six were external and nine were internal. And based on the correlation coefficient, 7 moderately correlated factors and 8 weakly correlated factors were derived.

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Specifically, among the factors in this study, technical efficacy and controllability were identified as having the greatest influence on information sharing among online community users ($k = 7$, $r = 0.450$, $p < 0.001$), which is inconsistent with the majority of scholars' findings that the key factors influencing information sharing among online community users are perceived usefulness and reciprocity and benefits, but supports the findings of different independent studies such as Jiang Z. Y. [25], Wang Y. F. and other different independent studies [34]. As can be seen from Table 3, external factors such as Technical efficiency and control, Information quality, Online relationship interaction, Institutional trust, variables that primarily act on the functional soundness of the platform and the atmosphere of community interaction, are mostly concentrated in the category of moderately relevant influencing factors. In contrast, internal factors such as Perceived usefulness, Subjective norms, and Self-efficacy accounted for only one-third of all moderately relevant influences.

Across all studies, Reciprocity and benefits (k=14), Perceived usefulness (k=11), Emotional support (k=10), and Online relational interactions (k=10) were all influences that were highly valued by the researchers and focused on for analysis. Among the different models, the above four are also the influencing factors that are of more concern to the model proposers and experimental validators. Combined with the conclusions drawn from this study, it can be found that the factors influencing the information sharing of online community users are mainly focused on the functional experience of the platform, perceived usefulness and information quality. Among the weaker influencing factors, the external factors include trust in online information and perceived privacy risk, which indicates that in the Internet era, online information is everywhere, and internet users' trust in online information and perceived privacy risk have already established a cognitive foundation when choosing online communities, and the information sharing behaviour, as a behaviour that lags behind platform use in time, has become much less strong. Meanwhile, among the six weakly correlated of internal factors, reciprocity and benefits, prestige effects, and altruistic desires may exist as moderating variables by category of online communities.

6. Conclusion

From a practical point of view, the advent of the Web 2.0 era has given birth to a large number of online communities, but behind their rapid development there are also many hidden problems. In the era of fragmentation and decentralization, users are constantly sharing and receiving information, but some of the online communities are not functional enough. For example, there are delays in receiving information; information is not intelligently pushed; and there are defects in basic functions such as liking, commenting, sharing, and rewarding. Therefore, for platform operators, the first step is to ensure the security and privacy of online information to gain the trust of users and to constantly upgrade the platform's functions and ease of use to address users' demands in terms of platform technology, so as to retain users to the greatest extent possible and thus promote user information sharing. In terms of perceived usefulness, information quality and self-efficacy, community managers should create a segmented space to attract users with different types of information sharing and information receiving needs, thereby improving the overall quality of community information. Not only that, from the perspective of traffic supply and bias, and from the perspective of reputation effect to create a group of quality head users used to attract new users, but also to support and encourage information sharing among new users and viewers, gradually forming a virtuous circle.

This study also has some limitations. Some of the effect sizes were included in a small literature leading to the risk of publication bias, and factors such as the length of the experiment, the subjects, and the experimental setting may have confounded the results. Also, moderating variables that lead to greater heterogeneity need to be analyzed further. A few factors, such as perceived implementation costs, only appeared twice (less than three times) in the independent sample and were not included in this meta-analysis, which may lead to less comprehensive conclusions.

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