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Motivators of Researchers' Knowledge Sharing and Community Promotion in Online Multi-Background Community

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ABSTRACT

As an essential group in knowledge innovation, researchers are encouraged to exchange ideas with each other for further brainstorm through advanced communication technology. However, efficient online knowledge sharing among researchers is still limited. Although past literature proposes a series of motivators of online knowledge sharing, the differences in the effects of motivators remain in dispute. Thus, it is time to understand how motivators influence each other and inspire scientists to share knowledge and promote virtual communities. Based on the self-determination theory, this study proposes a model with several factors and analyze 301 Chinese researchers' data in an online WeChat cross-disciplinary research community by adopting SmartPls 2.0 and SPSS 22. The results reveal the effects of several antecedents and mediating effects of altruism and knowledge sharing behavior and report the differences of results among different demographic groups. This study enriches the literature in knowledge sharing on social media and proposes further research points to researchers and useful advice to practitioners.

KEYWORDS

Community Promotion, Knowledge Sharing, Online Multi-Background Community

1. INTRODUCTION

As a type of products based on the communication and information technology (e.g., Web 2.0), social media, applications for information exchange and creation, provide people with multiple channels of knowledge diffusion and knowledge innovation (Kaplan & Haenlein, 2010; Filo et al., 2015). Through adopting social media, individuals can access knowledge faster and propose new ideas after exchanging their thoughts with others, indirectly achieving the individuals' self-development and promoting organizations (Filo et al., 2015). However, knowledge sharing behaviors do not naturally occur (Lu et al., 2006). Past researchers have explored motivators of knowledge sharing on social media based

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on different theories (e.g., social capital theory, technology acceptance model, social cognitive and social exchange theories) in broad contexts (Ahmed et al. 2018) and need more discussions as follows.

First, past researchers have adopted around 29 theories to explore knowledge sharing on social media. However, they fail to reach consensus in some effects of motivators (e.g., reputation, social factors, the norm of reciprocity, and altruism) and fail to adequately explore the quality and correlations of motivators (Gagne, 2009). Since knowledge cannot transfer from individual to individual naturally unless knowledge owners take the initiative to tell others (Welschen et al., 2012), people's willingness is vital to the initiation of sharing behavior. Deci and Ryan (1985) assert that externally induced incentives and internally evoked incentives can inspire behaviors, and different types of incentives have various qualities in inspiring behaviors. Different from the theories adopted in the past literature that used to focus on the relationship between motivators and knowledge sharing behaviors or intentions, the self-determination theory (Deci & Ryan, 1985) can be adopted to explore the online knowledge sharing phenomenon from the perspective of interactive effects of different motivations. Exploring the relationships among motivators may help researchers better understand the process of how knowledge sharing happens. Therefore, it is proper to adopt SDT to explore knowledge sharing behavior on social media. Second, although social media provide more approaches for researchers to exchange data (e.g., Birnholtz, 2007; Kaye et al., 2009), not enough papers have studied in how to inspire efficient knowledge exchange among academia who are the main contributors of knowledge innovation (Ahmed et al. 2018). Finally, out of taking knowledge competition advantage, researchers who are in the same field may less share knowledge with members. Fischer and Zigmond (2010) believe that the cross-disciplinary environment may inspire researchers to release the fear of losing advantages and exchange ideas with others. However, few past papers investigate researchers' knowledge sharing behaviors in a multidisciplinary virtual community on social media. Therefore, it is necessary to study how different motivators of knowledge sharing influence researchers with different major backgrounds in sharing knowledge in the cross-disciplinary community on social media.

This study introduces the background to the research in Part 2. Based on the theoretical background, the paper then proposes the hypotheses in Part 3. Next, this paper presents the research methods in Part 4. Part 5 and part 6 demonstrate the results. Next, the study discusses the contributions in Part 7. Finally, Part 8 concludes the whole study.

2. BACKGROUND

2.1 Knowledge

Ackoff (1989) categorizes "knowledge" into five types. The minimum concept is data (e.g., number, mathematical notations). Alavi and Leidner (2001) also support that data is the raw number or the fact with no direct meanings. As the second concept that integrates the data, information is about who, what, when, and where. Zack (1999) believes that information is the data described in specifically meaningful contexts. As the third concept, knowledge integrates information and data to answer issues about "how." Besides the above concepts, Ackoff (1989) also proposes the definition of understanding and wisdom. The understanding is the advanced stage of knowledge, and it is about to what extent people appreciate "why." As the most advanced level, wisdom evaluates the degree of understanding and adopts it into different contexts (Ackoff, 1989; Jennex and Bartczak, 2013; Jennex, 2017). As the milestone where symbols exist objectively and transfer to new knowledge synthetization (i.e., understanding) and the abstraction (i.e., wisdom), knowledge is the information used for interpretation, adoption, and judgment.

The previous literature has tried to systematically describe the "knowledge" from the perspectives of cognitive theory, instructional designed theory, and epistemological point (De & Ferguson, 1996). Referring to Ipe's (2003) work, this study investigates knowledge from the tacit aspect and explicit aspect. After Polanyi (1966) firstly proposes the concept of tacit knowledge, Nonaka (1994) defines it as know-how knowledge gained from individuals' experience. Generally, tacit knowledge is hard to transfer to people who do not have the same experience accurately (Hislop, 2002). Unlike implicit knowledge, explicit knowledge is defined as codified knowledge, and they can be expressed by words and reorganized. Compared with tacit knowledge, explicit knowledge can be stored, organized, and transferred to others 24-h and worldwide (Lam, 2000).

2.2 Knowledge Sharing and Importance for Researchers

Todorova and Mills (2018) define knowledge sharing as the action of knowledge providing and transferring among individuals in workplaces. Neumann and Prusak (2007) suggest that researchers should concern about the positive effect of knowledge networking in research activities to deal with the information explosion and changing contexts, promoting performance in cross-discipline scientific cooperation and collaborations. Furthermore, the interaction and integration among cross-disciplinary-cooperation may inspire new ideas (Fischer & Zigmond, 2010). The online platforms can help researchers access the knowledge exchange conveniently (e.g., Goecks et al., 2010; Parnell, 2011). Through social media, researchers can get data from others in the same fields and achieve new knowledge creation through "brainstorm" among people from different disciplines (Neumann & Prusak, 2007; Ward et al., 2013).

2.3 Theoretical Background

2.3.1 Theories of Knowledge Sharing on Social Media

With the development of communication and information technology, social media make people share knowledge more quickly and conveniently (Kaplan & Haenlein, 2010; Filo et al., 2015). Past literature has used around 29 theories or models to explore knowledge sharing behavior in the social media context (Table 1). Scholars have explored online knowledge sharing phenomenon from various perspectives of theories. This study roughly summarizes the theories into three streams. The first stream studies the knowledge exchange phenomenon from the perspective of new technology adoption and utilization (e.g., communication theory, adopting diffusion theory, technology acceptance model, task technology fit model, ISCM model, unified theory of acceptance and use of technology, IS success model, uses and gratification theory, lead user theory, and transactive memory system model). Scholars adopting these theories focus on exploring what motivators influence people's attitudes, intentions, and continuous intentions toward innovative service, technologies, and tools (e.g., social media platform). The second stream explores the relationship between people's beliefs, norms, or other psychological needs and their knowledge sharing intention (e.g., the theory of planned behavior, the theory of reasoned action, and the expectancy theory). Scholars in this stream mainly explore the knowledge sharing behavior from the "individual" standpoint, seldom considering the influences from outside. In contrary, scholars in the third stream usually include the factors related to society, environment or peers into the initiation of people's behaviors (e.g., attachment theory, commitment-trust theory, social exchange theory, social influence theory, critical mass theory, ERG theory, social capital theory, social cognitive theory, field theory, socialization and structuration theories, social learning theory, triandis theory, learning performance model, social support theory, social identity theory and theory of justice).

Past literature showed that different types of motivations (e.g., extrinsic or intrinsic motivations) have different levels of effects on people's behaviors in online platforms (e.g., Brabham, 2012; Kaufmann et al., 2011). In other words, not all motivators have similar effects on the initiations of people's behaviors. Since online knowledge exchange behavior is a kind of common online manner in virtual communities, its initiation may be influenced by different levels by different types of motivators. Most papers adopting the above theories only proposed the number of motivators of online knowledge sharing or knowledge sharing technology adoption (e.g., Wei et al.,2015; Tamjidyamcholo et al., 2014; Probodha & Vasanthapriyan, 2019; Okyere-Kwakye et al., 2019). For example, self-efficacy, attitude, satisfaction, affective commitment, outcome expectation, and sharing culture (Ahmed et al.,

Table 1. Theories of knowledge sharing on social media

Theory	Focus	Example
Communication Theory	Communication visibility (technique aspect) can influence knowledge sharing.	Leonardi (2014)
Attachment Theory	People's interactions with online communities' members can influence their behaviors	Chung et al. (2016)
Adopting the Diffusion Theory	Perceptions' perceptions toward technology influence technology adoption	Pillet and Carillo (2016)
ISCM Model	Satisfaction based on people's experience in using systems is the most important factor that leads to continuous use of applications	Hashim and Tan (2015)
Commitment-trust Theory	Trust in communities can influence people's behaviors	Hashim and Tan (2015)
Social Exchange Theory	People will conduct actions based on risks and benefits through exchanges among members.	Yan et al. (2016)
Social Influence Theory	Conformity, compliance, and obedience in social environments can influence people's behaviors	Papadopoulos et al. (2013)
Technology Acceptance Model	Users' perceptions influence users' decisions about using new technology	Bilgihan et al. (2016)
Critical Mass Theory	People may conduct collective behaviors to achieve collective good	Wang et al. (2016)
ERG Theory	Self-focused needs and relation-focused needs can influence intentions and behaviors	Hau and Kim (2011)
Lead User Theory	Leader users can be the main group of innovative services or products	Hau and Kang (2016)
Social Capital Theory	People's resources in social structures can influence their behaviors	Kwahk and Park (2016)
Social Cognitive Theory	Environments can influence people's affections, emotions, beliefs, and indirectly influence behaviors	Jin et al. (2015)
Theory of Reasoned Action	People's attitude and norms toward knowledge exchange influence intention and behavior	Gang and Ravichandran (2015)
Task Technology Fit Model	The match between technology and task influences performance and behavior	Lee and Lim (2011)
Unified Theory of Acceptance and Use of Technology	Users' expectancies, social influences and facilitating conditions influence intentions and behaviors	Kaewkitipong et al. (2016)
Theory of Planned Behavior	People's attitude perceived behavioral control and norms toward knowledge exchange influence intention and behavior	Alajmi (2012)
Field Theory	The interactions between the environment and people influence intentions and behaviors	Shang et al. (2017)
Expectancy Theory	People's expectancy, instrumentality, and valence influence their intentions	Behringer and Sassenberg (2015)
Socialization and Structuration Theories	Relationships among individuals, society, and agency and different relation models of human interactions can influence people's behaviors	Kaewkitipong et al. (2016)
Social Learning Theory	People's community practice, imitations influence learning, and behavioral intentions.	Alvino et al. (2011)
Triandis Theory	An exhaustive model that includes beliefs, attitudes, social influences in predicting behavioral intentions	Tamjidyamcholo et al. (2014)

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Table 1. Continued

Theory	Focus	Example
IS Success Model	The quality of systems influences people's satisfaction and behaviors	Alali and Salim (2013)
Learning Performance Model	Out of learning things and achieving performance, people will conduct social media activities (e.g., knowledge sharing)	Eid and Al-Jabri (2016)
Social Support Theory	Peoples' perceived social supports influence their intentions	Li et al. (2018)
Uses and Gratification Theory	People's values and awareness of active in using social media influence social media usage	Aisha et al. (2015)
Transactive Memory System Model	People's communication types and characteristics of system influence intentions	Chung et al. (2015)
Social Identity Theory	People's self-concepts derived from perceived membership in groups influence intentions and behaviors	Yen (2016)
Theory of Justice	Justice influences peoples' beliefs, attitudes, and intentions	Fang and Chiu (2010)

2018) show that the doubt and incongruence in differing these motivational factors still exist. Not enough papers have explained how motivators interact with each other and how different types of motivators influence final individuals' online knowledge sharing behaviors in various ways. Therefore, it is necessary to investigate the relationships among different motivators and distinguish differences among them in influencing individuals' online behaviors.

This study chooses to adopt the self-determination theory proposed by Deci and Ryan (1985) to investigate the relationships among different types of motivators of people's behaviors and the different influences of various motivators. Unlike past theories used in the literature, the self-determination theory focuses on the different effects of different types of motivations on people's behaviors. Researchers can use this theory to investigate people's volitional motivations (autonomous/self-determined ones and controlled/non-self-determined ones) in behavioral studies. Unlike autonomous motivations that generate out of people's curiosity, care, or values, controlled motivations are the incentives that inspire individuals to perform to satisfy their core-self needs and benefits (Cockrell & Stone, 2010). Ryan et al. (2008) believe that autonomous motivations will lead people to conduct self-determined behaviors as peoples satisfy basic psychological needs (autonomy, competence, and relatedness). Besides, Ryan et al. (2011) divide motivations into identified regulation, introjected regulation, external regulation, intrinsic motivation, and integrated regulation. Some research projects conducted based on SDT suggest that the effects of autonomous motivations are stronger than that of controlled motivations in inspiring knowledge sharing behaviors in organizations (e.g., Mitchell et al., 2012, Grolnick & Ryan, 1987; Cruz et al., 2009; Cockrell & Stone). However, studies have not reached this conclusion in the online knowledge sharing context. Thus, to clarify the contradict conclusions about the effects of some motivators of online knowledge sharing in literature and examine the validity of the above statement about relationships between autonomous motivations and controlled motivations in the online context, this study adopts autonomous motivation, controlled motivation, and introjected regulation into the research.

Through adopting the self-determination theory, this study can make several contributions. First, the self-determination theory's adoption will expand the application scope of this theory from general behaviors to online knowledge sharing behavior. Second, the self-determination theory's adoption will clarify some doubt and incongruence in motivators' effects on online knowledge sharing. Third, the self-determination theory's adoption will offer a new angle to researchers in studying the effects of motivators of online knowledge sharing. Researchers may further investigate the effects of relationships among different types of motivators on online knowledge sharing behaviors.

3. HYPOTHESES

3.1 Norm of Reciprocity (NR) as an External Regulation

Wu et al. (2006) define the norm of reciprocity, a motivation for individuals' social exchange, as a widely accepted idea that individuals should return on others who help them. As people hold this idea, they will believe that the more they help others, the more benefits they will gain. Since controlled motivation is related to individuals' self-benefits (Cockrell & Stone, 2010), reciprocity can be regarded as an external regulation or controlled motivation. Davenport and Prusak (1998) believe that reciprocity, as a control-oriented motivation, may impel people to share information with others to get further self-benefit. Past literature has verified the positive effect of reciprocity on knowledge sharing intention (e.g., Endres & Chowdhury, 2013; Todorova & Mills, 2018). Additionally, previous researchers have asserted that if an intense sensation of reciprocity in knowledge sharing exists in online organizations, the communication among members will be active, and the performance of the whole organization will be better (Wasko & Faraj, 2005). In the online research community context, if researchers have high-level norms of reciprocity, they may help others seek further returns or help from others in materials and experience. Thus, this study hypothesizes that:

Hypothesis 1: The norm of reciprocity contributes to knowledge sharing behaviors.
H1a: The norm of reciprocity contributes to implicit knowledge sharing.
H1b: The norm of reciprocity contributes to explicit knowledge sharing.

3.2 Reputation (RP) as an Introjected Regulation

As an intangible asset, reputation is defined as the general judgments of the public about someone or some entities (Safa & Von Solms, 2016). If an individual's performance fails to match others' expectations, the individual will get negative public judgments. Ba, Stallaert, and Whinston (2001) believe that great fame can help individuals to get higher status and maintain prestige among people. Thus, individuals will try their best to perform well to maintain the right images (i.e., implicit consequence) in public under pressure. Since outside pressure (i.e., comments) will influence people's behavior in maintaining reputation, reputation can be regarded as an introjected regulation that influences behaviors with outside pressure (Gagne, 2009). For researchers, reputations are incredibly significant because fame, to some extent, represents the authority in specific fields and the chance of being respected and accepted by others or journals (Cetina, 1999; Wasko & Faraj, 2005). Out of the purpose of maintaining respect from others, it is easy to understand that researchers are willing to gain more knowledge to catch up with other famous researchers or stay ahead in specific fields. Furthermore, He and Wei (2009) and Todorova and Mills (2018) have verified that reputation can contribute to knowledge sharing. For the researchers, they must face competitions from other scientists and industrial fields all the time. Only the more latest research findings researchers present to people, more recognition they can acquire. Therefore, if researchers perceive their reputation as high-level, they will be more willing to collect new knowledge to maintain their professional advantages and share knowledge to enhance their reputation further. Therefore, this study hypothesizes that:

Hypothesis 2: Reputation contributes to knowledge sharing.
H2a: Reputation contributes to explicit knowledge sharing.
H2b: Reputation contributes to implicit knowledge sharing.
H3: Reputation is positive to the intention to collect knowledge

3.3 Anticipated Relationship (AR) as an Introjected Regulation

Introjected regulation assumes that individuals will perform well to enhance implicit results (Ryan et al., 2011). CROPANZANO et al. (2017) believe that as people communicate with others, they may expect to gain better interpersonal relationships that are implicit tangible assets for further work. In this study, the anticipated relationships (AR) are adopted to describe this kind of relationship among researchers. In social media and virtual community contexts, the anticipated relationships can be adopted the definition from Bock et al. (2005) as the perceptions of mutual interpersonal relationships.

Zhang et al. (2017) believe that perceived interpersonal social relationships are the primary motivation of knowledge contributions (e.g., releasing data, ideas, and information). As people conduct knowledge networking with others, they will enhance their social ties with others and have more supports in the future. To enhance these social connections with others, people will improve more active social interactions (He and Wei, 2009). On this occasion, the anticipated relationships can be regarded as an introjected regulation that inspires people to conduct particular behavior for implicit consequences. In this study, if a researcher has high-level perceived anticipated relationships, he/she will more prefer to share resources or experience with others, aiming to gain more professional connections in the career. Therefore, this study hypothesizes that:

Hypothesis 4 Anticipated relationships contribute to knowledge sharing behavior.
H4a: Anticipated relationships contribute to explicit knowledge sharing behavior.
H4b: Anticipated relationships contribute to implicit knowledge sharing behavior.

3.4 Altruism (ALT) as an Autonomous Motivation

Hsu and Lin (2008) define altruism as the extent to which individuals are willing to enhance others' welfare without return expectations. Constant and the co-authors (1996) believe that individuals may perform self-scarification to satisfy their intrinsic desires. As an intrinsic motivation, altruism has been verified as the incentive to share knowledge (Fang & Chiu, 2010; Hsu & Lin, 2008; Shang, 2014). In this study, if researchers perceive helping others as an essential belief and regard the knowledge as valuable benefits for others, they will convey the ideas and materials to other researchers. Therefore, this study hypothesizes that:

Hypothesis 5 Altruism contributes to sharing knowledge.
H5a Altruism contributes to implicit knowledge sharing.
H5 b Altruism contributes to explicit knowledge sharing.

3.5 Controlled Motivation, Autonomy-Oriented Motivation, and Introjected Regulation

The SDT research indicates that control-oriented motivations can affect autonomy-oriented motivations (e.g., Newby & Alter, 1989; Vansteenkiste et al., 2007). Many studies indicate that external controls of a particular behavior will hinder the autonomy-oriented motivations because the former will prevent the sense of autonomy (e.g., Deci & Ryan, 2000; Deci et al., 1999; Lian et al., 2012; Cockrell & Stone, 2010). Past literature has tried to discuss the relationships between two types of motivations. Sheldon et al. (2003) believe that when extrinsic rewards are set to restrain particular behavior, these extrinsic rewards may lead to high pressures and undermine employees' autonomy-oriented motivations. However, implicit rewards (i.e., introjected regulations) for cultivating particular behavior will satisfy individuals' psychological needs and positively impact autonomy-oriented motivations. In this study, when reciprocity is the primary motivator of researchers' knowledge sharing behavior, researchers will less consider voluntarily helping others without returns. However, when reputation and anticipated relationships are the primary motivators of researchers' knowledge sharing behavior, researchers will help others with less selfishness, aiming to maintain their good public images and improve stronger social ties with others. Thus, the hypotheses are formatted.

H6 Reciprocity is detrimental to altruism
H7 reputation is positive to altruism
H8 Anticipated relationships are positive to altruism

3.6. Trust (T)

Trust is defined as the individuals' expectancy and intention of relying on others (Moorman et al., 1992). Trust is the central role in forming relationships and collaborations among people (Achrol, 1991; Nahapiet & Ghoshal, 1998). Blau (1964) asserts that trust plays a vital role in this exchange process among people's communications. Through these cooperative interactions, people may more show their ideas and exchange information with others and believe others for further collaboration or communication. In the organizational context, trust may create a climate for knowledge sharing. Abrams et al. (2003) confirm that employees become more willing to participate in knowledge-sharing when they feel trust and rely on each other. In online communities, if members trust each other, they may accept others' suggestions and adopt the advice. In the meanwhile, members may more prefer to share their ideas or experience with others to solve problems. Therefore, this study hypothesizes that:

Hypothesis9: Trust can predict the knowledge contributing behavior of members.
H9a: Trust can predict implicit knowledge sharing.
H9b: Trust can predict explicit knowledge sharing.
Hypothesis 10: Trust can predict the knowledge collecting behavior of members.

3.7. Knowledge Contribution and Collecting Behavior (COLLECT) and Community Promotion (CP)

Chen and Hung (2010) believe that social interaction and information exchange are common phenomena in online communities. Through these interactions and exchanges, members of communities will feel support from each other and generate the intention to help each other (Bulter, 2001). In online communities, since interactions and exchanges can provide researchers with support and knowledge, they may have intentions to help members get more support from outside. Thus, to help members more, researchers in the online communities may tend to invite more people to join the group for further interaction and communication. Meanwhile, since the more people conduct information spread, and social interactions, the more intense and frequent knowledge exchange will happen. To gain further knowledge exchange and social support, researchers may try to access more resources by inviting newcomers into groups (Chen & Hung, 2010). Thus, this study hypothesizes that:

Hypothesis 11: Knowledge sharing can predict community promotion.
H11a: Implicit knowledge sharing can predict community promotion.
H11b: Explicit knowledge sharing can predict community promotion.
Hypothesis12: Knowledge collecting behavior can predict community promotion.

4. RESEARCH METHODOLOGY

4.1 Sampling

This study regarded online active Chinese researchers as population and researchers in WeChat communities as the sampling frame. As a mobile also laptop-used all-in-one messaging application, people can access WeChat anytime and anywhere (Lam, 2019). Besides, 90% of people who participate in the survey about WeChat usage admit that WeChat is their top choice for daily work communication (Jing, 2018). Thus, this study chooses WeChat online communities as a focused platform. Among all the research WeChat communities, this study conducted a purposive sampling approach to choose "Growing Group" from "Lao Ta league of research," one of the most prominent Chinese research virtual communities established by Pro. Chuanyang Yu from Yanshan University. Then, this study conducted surveys by random sampling in the WeChat group to observe users' attitudes. Volunteers with different major backgrounds from diversified types of universities filled the Wenjuanxing online survey (https://www.wjx.cn/, a Chinese famous online survey company) with paying 5 Yuan RMB as a reward on 10th August 2018. Finally, 301 people were enrolled in the survey (61.934% of the whole group). According to the criteria proposed by Hair, Ringle, and Sarstedt (2011) and Krejcie and Morgan (1970), the sample size of the case is acceptable.

4.2 Instrument

This study conducted quantitative research by self-reported online questionnaires. All variables were measured with a five-point Likert scale adapted from the past literature, dividing them as follows. 1) six items for demographic variables (gender, age, educational level, field, and university type and WeChat account); 2) three items for the norm of reciprocity from Lin, Hung, and Chen (2009); 3) three items for anticipated relationships from Bock et al. (2005); 4) three items for reputation from Hsu and Lin (2008); 5) two items for altruism from Kankanhalli, Tan, and Wei (2005); 6) three items for sharing implicit knowledge and two items for sharing explicit knowledge from Bock et al. (2005); 7) three items for trust from Hsu and Lin (2008), Lin (2008), Palvia (2009) and Ridings et al.,(2002); 8) one item for knowledge collecting behavior from Chen and Hung (2010); and 9) four items for community promotion from Koh and Kim (2004).

Two professional translators who worked in a translation company in Ningbo, China, translated the Chinese version of the survey and proofread to ensure translation equivalence (Beaton et al., 2000). Two translators who worked in an IELTS training and foreign language training school in Ningbo, China, translated the Chinese version into English. After the above two steps, a Professor in management from Xi'an Jiaotong-Liverpool University assessed the quality of the questionnaire to confirm the semantic equivalence and idiomatic equivalence (Beaton et al., 2000). Finally, ten Chinese students studying at Xi'an Jiaotong-Liverpool University, and eight English native speakers studying at the University of Nottingham, Ningbo, China, reviewed the surveys to report the ambiguous points.

4.3 Participants

This study divided participants (Table 2) into several categories based on different demographic features (gender, age, educational level, filed, and university type). The number of males (130, 43.189%) was 41 less than the number of females (171, 56.811%). Subsequently, 48.505% of participants were 25-29 years old, and no one was 45-50 years old. 29.236% of people were 20-24 years old. 12.292% of people were 30-34 years old. 5.648% of people were 35-39 years old. 3.987% of people were 40-44 years old. Then, 73.422% of participants were Master's degree holders, and the rest of the participants were Doctor's degree holders. Finally, the number of participants majoring in law took up the most substantial proportion (17.276%), followed by management (15.282%), engineer and education (both are 12.957%), economy (8.970%), science (8.306%), literature (6.645%), philosophy (6.312%), art (4.983%), medicine (3.322%), history (1.661%), agriculture (0.997%) and military science (0.332%). Besides, more than 89% of participants were in Chinese universities, and the rest of them were in overseas universities.

Table 2. Demographic information

Issue	Number
Gender	
Male	130
Female	171
Age	
20-24	88
25-29	146
30-34	37
35-39	17
40-44	12
45-50	0
Education	
Master	221
Doctorate	80
Research field	
Law	52
Management	46
Engineer	39
Education	39
Economy	27
Science	25
Literature	20
Philosophy	19
Art	15
Medicine	10
History	5
Agriculture	3
Military	1
University	
Domestic	268
Oversea	33

4.4. Data Analysis

This study conducted descriptive statistics and correlation analysis with SPSS 22. This study then adopted a variance-based SEM using the PLS method (PLS-SEM) to assess scales and examine hypotheses (Hair, 2017). Finally, this study examined the potential mediating effect with SPSS PROCESS.

Table 3. The norm of reciprocity is positively correlation

	Mean	SD	Skewness	Kurtosis	K-S	S-W	1	2	3	4	5	6	7	8
AR	4	0.789	-0.638	0.649	0.129**	0.921**								
RP	3.96	0.823	-0.606	0.551	0.13**	0.921**	.688**							
ALT	4	0.768	-0.583	0.57	0.176**	0.907**	.600**	.599**						
T	3.42	0.894	-0.127	-0.093	0.124**	0.962**	.450**	.390**	.431**					
NR	3.802879291	0.829265079	-0.465	0.405	0.14**	0.933**	.468**	.461**	.545**	.618**				
EK	3.73	0.923	-0.426	0.017	0.148**	0.919**	.484**	.447**	.503**	.489**	.616**			
IK	3.9	0.758	-0.391	0.441	0.166**	0.923**	.522**	.486**	.540**	.496**	.663**	.775**		
CP	3.62	0.879	-0.363	0.193	0.126**	0.949**	.547**	.545**	.451**	.555**	.570**	.631**	.652**	
COLLECT	1.68	1.06	1.91	3.205	0.319(0.000)	0.66(0.000)	.177**	.208**	.142*	.212**	.160**	.180**	.132*	.245**

Note: * p < 0.05; ** p < 0.01. K-S: Kolmogorov-Smirnova. S-W: Shapiro-Wilk.

5. RESULTS

5.1 Descriptive Statistics and Correlations

SPSS software 22.0 was used to conduct descriptive statistics and correlation analysis. Spearman's correlation was applied because the normality test showed that the data were non-normally distributed (p-value=0.000<0.5). The correlation analysis roughly supported all the hypotheses except Hypothesis 6. Table 3 shows that the norm of reciprocity is positively correlated with implicit knowledge sharing (r=0.663, p-value<0.01) and sharing explicit knowledge (r=0.616, p-value<0.01), respectively. Reputation is positively correlated with explicit knowledge sharing (r=0.447, p-value<0.01), sharing implicit knowledge (r=0.486, p-value<0.01) and knowledge collecting behavior (r=0.208, p-value<0.01), respectively. Anticipated relationships are positively correlated with explicit knowledge sharing behavior (r=0.484, p-value<0.01) and implicit knowledge sharing behavior (r=0.522, p-value<0.01), respectively. Altruism is positively correlated with implicit knowledge sharing (r=0.540, p-value<0.01) and explicit knowledge sharing (r=0.503, p-value<0.01), respectively. Trust is positively correlated with implicit knowledge sharing (r=0.496, p-value<0.01) and explicit knowledge sharing (r=0.489, p-value<0.01), respectively. Implicit knowledge sharing (r=0.652, p-value<0.01), explicit knowledge sharing (r=0.631, p-value<0.01) and knowledge collecting behavior (r=0.245, p-value<0.01) are all positively correlated with community promotion. Reputation is positively correlated with altruism (r=0.599, p-value<0.01). Anticipated relationships are positively correlated with altruism (r=0.600, p-value<0.01). However, reciprocity is not negatively correlated with altruism (r=0.545>0, p-value<0.01).

Since this study applies the self-report questionnaire to collect all the data about independent and dependent variables from the same group people, the influence of common method variance should be concerned (Podsakoff et al., 2003). Harman's single factor test shows that the variance of principal component interpretation accounts for less than 50% (48.698%) of the variance, reflecting that the common method bias is not very serious.

Table 4. Reliability and convergent validity

Construct	Items	Outer loading	Cronbach's Alpha	Composite Reliability	AVE
		>0.7	>0.7	>0.7	>0.5
ALT	ALT1	0.878	0.720	0.877	0.781
	ALT2	0.889			
AR	AR1	0.865	0.866	0.918	0.789
	AR2	0.918			
	AR3	0.880			
EK	EK1	0.951	0.900	0.952	0.909
	EK2	0.955			
IK	IK1	0.897	0.882	0.927	0.809
	IK2	0.878			
	IK3	0.923			
NR	NR1	0.880	0.890	0.931	0.819
	NR2	0.929			
	NR3	0.906			
RP	RP1	0.891	0.848	0.908	0.767
	RP2	0.868			
	RP3	0.869			
CP	CP1	0.86	0.901	0.931	0.772
	CP2	0.879			
	CP3	0.904			
	CP4	0.87			
T	T1	0.864	0.871	0.921	0.795
	T2	0.888			
	T3	0.922			

Table 5. Fornell-Larcker

ALT	0.884								
AR	0.619456	0.89							
CP	0.497791	0.58	0.88						
T	0.471491	0.47	0.59	0.891					
IK	0.583561	0.58	0.67	0.531181	0.9				
Collect	0.11844	0.18	0.23	0.239174	0.149397	1			
EK	0.510892	0.52	0.65	0.50636	0.782882	0.176	0.953		
NR	0.591652	0.51	0.58	0.643785	0.675868	0.165	0.597876	0.905	
RP	0.6371	0.7	0.59	0.4358	0.5492	0.204	0.4781	0.49699	0.876

Table 6. Hypotheses test with female data and male data

Hypotheses	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/ STERR|)	Conclusion
H1a: NR-IK	0.404567	0.406120	0.078144	5.177191	Support
H1b: NR-EK	0.328040	0.331116	0.082652	3.968931	Support
H2a: RP-EK	0.068837	0.070535	0.069509	0.990326	Not support
H2b: RP-IK	0.103971	0.103564	0.061686	1.685498	Support
H3: RP-COLLECT	0.122844	0.123189	0.052975	2.318916	Support
H4a: AR-EK	0.174811	0.169590	0.083938	2.082617	Support
H4b: AR-IK	0.183321	0.180746	0.070730	2.591839	Support
H5a ALT-IK	0.126107	0.124009	0.071653	1.759962	Support
H5 b ALT-EK	0.100386	0.100396	0.074547	1.346616	Support
H6 NR-ALT	0.314836	0.314497	0.055178	5.705842	Not support
H7 RP-ALT	0.310678	0.309920	0.061846	5.023434	Support
H8 AR-ALT	0.241424	0.242062	0.066546	3.627931	Support
H9a: T-IK	0.080313	0.083567	0.053773	1.493572	Support
H9b: T-EK	0.136177	0.137905	0.063913	2.130647	Support
H10: T-COLLECT	0.185636	0.184060	0.054695	3.393999	Support
H11a: IK-CP	0.399022	0.400778	0.081277	4.909400	Support
H11b: EK-CP	0.322478	0.322077	0.082607	3.903758	Support
H12: COLLECT-CP	0.110642	0.109790	0.039437	2.805539	Support

5.2 Measurement Model

After the algorithm convergence reaches in three iterations with a stable estimation (Garson, 2012), the measurement model is assessed based on several indexes (Hair et al., 2016). Table 4 shows that Cronbach's Alpha of the constructs in this research range from 0.720 to 0.901, and composite reliability values range from 0.877 to 0.952, suggesting a good level of reliability. The minimum AVE value is 0.767 (higher than 0.5), and the outer loadings of instruments meet the critical criteria (higher than 0.70), supporting the satisfactory level of convergent validity. The Fornell-Larcker method (Table 5) shows a good level of discriminant validity of the measurement model.

5.3 Structural Model

5.3.1 Hypotheses Testing

A 5000-time bootstrapping was applied to test the hypotheses (Vinzi et al., 2010). The results show that: The norm of reciprocity contributes to implicit knowledge sharing (Original Sample=0.405; p-value<0.01) and explicit knowledge sharing (Original Sample=0.328; p-value<0.01); thus, H1 is supported. Reputation is positive to intention to collect knowledge (Original Sample=0.123; p-value<0.01) and implicit knowledge sharing (Original Sample=0.104; p-value<0.1), respectively. Thus, H3 and H2b are supported. Anticipated relationships contribute to explicit knowledge sharing behavior (Original Sample=0.175; p-value<0.01) and implicit knowledge sharing (Original Sample=0.183; p-value<0.01), respectively. Thus, H4 is supported. Altruism contributes to implicit knowledge sharing (Original Sample=0.126; p-value<0.1) and explicit knowledge sharing behavior

Table 7. Mediation test results

Path	Sobel test	Bootstrapping β	Confidence interval (95%)	
			Lower	Upper
RP→COLLECT→CP	1.9190 (0.0550)	0.0245	0.0046	0.0529
T→IK→CP	7.4516 (0.000)	0.2543	0.1866	0.3386
T→EK→CP	7.1421 (0.000)	0.2350	0.1687	0.3167
T→COLLECT→CP	1.6955 (0.0900)	0.0215	0.0016	0.0487
Note: number in "()" is the p-value. The value in the Sobel test column is Z value.				

(Original Sample=0.100; p-value<0.1), respectively. Thus, H5 is supported. Reputation is positive to altruism (Original Sample=0.311; p-value<0.01). Thus, H7 is supported. Anticipated relationships are positive to altruism (Original Sample=0.241; p-value<0.01). Thus, H8 is supported. Trust is positive to the implicit knowledge sharing (Original Sample=0.080; p-value<0.1) and explicit knowledge sharing behavior (Original Sample=0.136; p-value<0.01), respectively. Thus, H9 is supported. Trust is positive to the knowledge collecting behavior (Original Sample=0.186; p-value<0.01). Thus, H10 is supported. Implicit knowledge sharing (Original Sample=0.399; p-value<0.01) and explicit knowledge sharing behavior (Original Sample=0.322; p-value<0.01) are positively related to community promotion. Thus, H11 is supported. Knowledge collecting behavior is positively related to community promotion (Original Sample=0.111; p-value<0.01). Thus, H12 is supported.

However, reciprocity is positive to altruism (Original Sample=0.315; p-value<0.01). Thus, H6 is not supported. Reputation fails to predict explicit knowledge sharing (Original Sample=0.069; t=0.983); thus, H2a is not supported. Table 6 shows the summary of the conclusion of hypotheses testing.

5.3.2 Effect Size

In the model, five endogenous variables (altruism, explicit knowledge sharing behavior, implicit knowledge sharing behavior, and community promotion) have R square values of 0.534, 0.440, and 0.553, and 0.503, respectively, showing an acceptable predictive accuracy of the structural model (Hair et al., 2014). However, the R square value of knowledge collecting behavior is 0.069, which reflecting that the predictive accuracy of the structural model in the paths from independent variables to knowledge collecting behavior is not such accurate.

Q square is also applied to measure the degree of effect of predictors on consequence (Wong, 2013). The results show that the value of the Q square of community promotion is 0.371 (more than 0.35), which means exogenous construct has large predictive relevance for this endogenous latent variable. The value of the Q square of implicit knowledge sharing is 0.437 (more than 0.35), which means exogenous construct has large predictive relevance for this endogenous latent variable. The value of the Q square of knowledge collecting behavior is 0.065 (more than 0.02 and less than 0.15), which means exogenous construct has small predictive relevance for this endogenous latent variable. The value of the Q square of explicit knowledge sharing is 0.379 (more than 0.35), which means exogenous construct has large predictive relevance for this endogenous latent variable. The results show that the value of the Q square of altruism is 0.401 (more than 0.35), which means exogenous construct has large predictive relevance for this endogenous latent variable.

Table 8. Serial multiple mediation test

	Mediating test by PROCESS			
Path	Direct effect	95% Confidence interval	Indirect effect	95% Confidence interval
AR→ALT→EK→CP	0.3256	[0.2067, 0.4445]	0.0968	[0.0522, 0.1617]
AR→ALT→IK→CP	0/.3052	[0.1836, 0.4268]	0.1210	[0.0739, 0.1865]
NR→ALT→EK→CP	0.2617	[0.1442, 0.3792]	0.0670	[0.0352, 0.1198]
NR→ALT→IK→CP	0.2226	[0.0978, 0.3474]	0.0826	[0.0497, 0.1368]
RP→ALT→EK→CP	0.3548	[0.2427, 0.4669]	0.1104	[0.0673, 0.1743]
RP→ALT→IK→CP	.3299	[0.2149, 0.4448]	0.1310	[0.0827, 0.2007]

6. POST-HOC ANALYSIS

6.1 Mediation Analysis

Besides examining the hypotheses, SPSS PROCESS was applied to verify the mediation based on 5000-time bootstrap resampling (Preacher & Hayes, 2008).

6.1.1 Mediation Test

Results show that the 95% confidence interval for the direct effect between reputation and community promotion is [0.5003, 0.7004], excluding 0. Subsequently, the 95% confidence interval for the direct effect between trust and community promotion is [0.2530, 0.4334], excluding 0.

For indirect effects, Table 7 shows that all the 95% confidence intervals for indirect effect exclude 0, suggesting that the mediating effects exist. Furthermore, the p-values of the Sobel tests (p=0.000) also confirm the mediating effects (Sobel, 1982). Thus, knowledge collecting behavior mediates the effect of reputation and trust on community promotion, respectively. Additionally, implicit knowledge sharing behavior and explicit knowledge sharing behavior mediate the effect of trust on community promotion.

6.1.2 Serial Multiple Mediation Test

Table 8 shows that the anticipated relationship has a positive direct effect on community promotion (the 95% confidence interval for direct effect is [0.2067, 0.4445], excluding 0). Subsequently, reciprocity has a positive direct effect on community promotion (the 95% confidence interval for direct effect is [0.1442, 0.3792], excluding 0). For indirect effects, all the 95% confidence intervals for indirect effect

Table 9. Gender groups, p-values

MANN-WHITNEY U Gender		
Variable	Sig.	Difference
CP	0.038	YES
AR	0.020	YES
RP	0.002	YES
KRUSKAL-WALLIS Age		
T	0.025	YES

Table 10. Hypotheses test with female data and male data

Path	Original Sample (O)		T Statistics (|O/STERR|)	
	Female	Male	Female	Male
ALT -> EK	0.036626	0.223367	0.482195	1.596143
ALT -> IK	0.094395	0.234319	1.213591	1.857863
AR -> ALT	0.282539	0.139487	3.465308	1.400052
AR -> EK	0.137292	0.285375	1.43447	1.692016
AR -> IK	0.129567	0.283359	1.497285	2.137635
COLLECT -> CP	0.113445	0.072472	1.934834	1.22991
EK -> CP	0.519916	0.195803	4.663963	1.726347
IK -> CP	0.129836	0.621007	1.158391	6.150616
T -> COLLECT	0.159657	0.226921	1.984443	2.891384
T -> EK	0.105539	0.16129	1.232819	1.500272
T -> IK	0.10801	0.037172	1.532921	0.399453
NR -> ALT	0.230741	0.406953	3.596866	4.465273
NR -> EK	0.424424	0.163767	5.189369	1.016852
NR -> IK	0.446298	0.308719	5.558879	2.008397
RP -> ALT	0.335447	0.341271	4.427251	3.902261
RP -> COLLECT	0.116819	0.09718	1.485613	1.345318
RP -> EK	0.140684	-0.058299	1.649629	0.450365
RP -> IK	0.105493	0.036225	1.232678	0.377594

exclude 0, suggesting that the mediating effects exist. Thus, the serial multiple mediating effects of altruism, knowledge sharing exist.

6.2 The Difference Among Groups

This study firstly applied the non-parametric approach to compare the difference of responses among groups (Pallant, 2013) to investigate the differences in attitudes among groups. Results show that only gender and age had influences on people's attitudes. Table 9 shows among the gender groups, the p-values of the MANN-WHITNEY U test of community promotion, anticipate relationships, and reputation are less than 0.05, suggesting the existence of significant differences. Furthermore, among the gender groups, the p-values of the KRUSKAL-WALLIS test of trust is less than 0.05, suggesting a significant difference.

To further investigate the differences of gender and age on attitudes toward surveys, this study analyzed the data sets separately to investigate the significance of the paths. Table 10 shows some differences exist between the significance of the paths based on the females' data set and the males' data set. To be specific, based on the female data set, H1b, H11b are supported, while the results based on males' data set reject these conclusions. In contrast, the results based on males' data set support the H4b, H11a, while the results of the females' data set do not get the same conclusions. For H8, although the results based on both data sets get the same conclusion, they propose the verdict based on different reasons. The result of the females' data set shows that anticipated relationships are positive to altruism, which rejects the hypothesis. However, the results based on the males' data set show that no significant relationship exists between anticipated relationships and altruism.

Table 11. Hypotheses test with different age groups data

Path	Original Sample (O)				T Statistics			
	Age 1	Age2	Age3	Age 4	Age 1	Age2	Age3	Age 4
ALT->EK	0.096022	0.172894	-0.084735	0.051096	0.662047	1.873588	0.297466	0.181504
ALT->IK	0.288671	0.134301	-0.156036	-0.079373	2.012116	1.860799	0.486491	0.349683
AR->ALT	0.103663	0.319622	0.571666	0.201266	1.020923	3.429912	2.934365	1.268815
AR->EK	0.164781	0.089139	0.24468	0.269716	1.077991	0.837724	0.717733	0.91456
AR->IK	0.17255	0.017866	0.569902	0.350871	1.816591	0.186826	1.571286	1.404064
COLLECT->CP	0.125809	0.090585	0.152732	0.117456	2.148807	1.274343	1.637831	0.722668
EK->CP	0.606487	0.168598	0.337108	0.074406	4.315413	1.538445	1.499857	0.360485
IK->CP	0.136356	0.560183	0.411129	0.604996	0.842754	5.695392	1.690429	3.237915
T->COLLECT	0.003021	0.178505	0.305921	0.334933	0.024565	2.058227	2.11634	2.341047
T->EK	0.175692	0.172013	0.14491	0.090109	1.159885	2.36983	0.492831	0.310113
T->IK	0.140729	0.130152	0.08798	-0.002916	1.203802	2.423949	0.313974	0.012302
NR->ALT	0.355234	0.220282	0.430162	0.433326	3.39913	3.085302	2.483571	2.556137
NR->EK	0.28857	0.388377	0.06307	0.418042	1.333079	4.754447	0.171759	1.336184
NR->IK	0.246083	0.52395	0.09961	0.683801	1.269897	7.377386	0.361296	3.022101
RP->ALT	0.401343	0.328995	-0.169005	0.342311	4.036324	3.931225	0.873198	1.767138
RP->COLLECT	0.149232	0.118292	0.085761	0.107839	1.620424	1.518965	0.564977	0.497721
RP->EK	0.093732	0.047592	0.180281	-0.050641	0.669421	0.510683	0.735967	0.197806
RP->IK	0.087601	0.175417	-0.091179	-0.026422	0.684501	2.177069	0.372347	0.115207

Table 11 shows the results of hypotheses testing based on different age interval data sets. This study divided the whole people into four groups (i.e., 20-24 years old, 25-29 years old, 30-34 years old, and more than 34 years old). The results based on the Age 1 data set show that H5a,H12,H11b and H7 are supported. The results based on the Age 2 data set show that H5 b, H8, H11a, H10, H9, H1, H7, and H2b are supported. The results based on the Age 3 data set show that H8 and H10 are supported. The results based on Age 4 data set show that H11a, H10, and H1a are supported.

7. DISCUSSIONS

7.1 Findings from Surveys

Based on the analysis from 301 samples, this study shows that: 1. The norm of reciprocity contributes to knowledge sharing. 2. Reputation is positive to the intention to collect knowledge and implicit knowledge sharing, respectively. 3. Anticipated relationships contribute to knowledge sharing and altruism, respectively. 4. Altruism contributes to knowledge sharing. 5. Reputation is positive to altruism. 6. Trust is positive to knowledge sharing and knowledge collecting behavior, respectively. 7. Knowledge sharing and knowledge collecting behavior are positively related to community promotion. Besides, this study finds out the mediating role of knowledge collecting behavior in the effect of reputation and trust on community promotion; and the serial multiple mediating effects of implicit knowledge sharing and explicit knowledge sharing in the path between trust and community promotion. Finally, this study also finds the influences of gender and age on main paths.

7.2 Supplement Interviews

This study conducted interviews as supplements for the survey study. Ten researchers (Appendix A shows the demographic information) joined in the interview stage. The interview was conducted through the WeChat voice call feature by asking open-ended questions. The interviews were recorded by WeChat, transcribed by the researchers, and proofread by the interviewees. All the interviewees answered the following questions openly in the semi-structured interview stage: 1. Will you share your experience with others in the group, and why or why not? 2. Do you think you are respected by others? 3. Will you share the materials and information you learned from working and study? 4. Is “helping others for enjoyment” the motivation for your knowledge sharing behavior? 5. Have you tried to cooperate with members? Do you think that telling others about your experience may create opportunities in cooperation?

7.2.1 Reputation and Knowledge Sharing

Interviewees explain what they perceived reputation and why they do not want to share knowledge. The reason is: the respect from the virtual group is not the “reputation” that they want. People prefer to chase reputations in the real world from colleagues and leaders. For example, Participant A said, “I don’t need any reputation from virtual group members, and I am a green hand in the research field. I feel grateful to learn a lot about research from the group, not to get respect from others, but to catch up with others.” Participant J also agreed that “Learning more will help you stay ahead and get more respect from others in the real world. Comparing answering others’ simplest questions and showing you are a pompous guy, it is more meaningful to show what you have in publications to win respect from colleagues.” The finding is in line with Wei, Chen, and Zhu (2015), who found that reputation did not affect knowledge sharing unless the “reputation” as a measure for evaluating the members’ status in the group. In other words, few people will contribute knowledge out of maintaining a virtual reputation unless a virtual reputation determines the membership of online group members. The study of Fischer and Zigmond (2010) also supports the finding. They found that researchers might decline the knowledge sharing with others to keep comparative advantages and reputation in the job market.

7.2.2 Reciprocity, Altruism and Knowledge Sharing

Interviewees’ responses also explained why the effect of reciprocity on altruism was positive. Altruism is a complex phenomenon. Purely scarifying self-interests and helping others are not accepted by the people. Most people think that their helping behaviors are out of other purposes. Therefore, the relationship between altruism and sharing is not affirmative; instead, it is dynamic. In contrast, the expectation for return may lead to pretend to be selfless. For example, Participant F said, “Although I share some documents or experience with others, I still want to get some similar responses from others before I share. Pure self-scarification is not a legitimate reason for sharing things with others.” Participants B also supported that, “At this age, doing something only for others is hard. Many people, including me, will evaluate to what extent they can get return before giving. Almost no one has such kind-hearted. Otherwise, he will be a tool. Most people give others something because they expect to get some return”. Compared with altruism, anticipated return and social tie may more lead them to perform altruistically share the knowledge. The responses show that before performing selfless to others, people will consider whether they have close relationships with others and have a high possibility of gaining benefit in return. This finding is in line with the study of Papadopoulos, Stamati, and Nopparuch (2013), showing that pure altruism was not the most important motivator of knowledge sharing. Finding also reveals that the general existence of reciprocal altruism and contingency between action and reciprocation in human society (Schino & Aureli, 2009).

7.3 Implications

This study makes several contributions to the literature. Firstly, it contributes to the literature in knowledge sharing on social media by examining the application of the self-determination theory. Although past studies have explored the effects of various motivators of individuals' online knowledge sharing behaviors, they mostly neglect the effects of different types of motivation. The research model tests the relationships between motivations and online knowledge sharing based on motivations' controlled-to-autonomous continuum. Besides, controlled motivations have critical effects on autonomy-oriented motivations, while few papers have investigated this assumption in the online knowledge sharing context. The study sheds light on the application of the self-determination theory in online knowledge sharing research. The application of SDT in this study can be referred to by future studies to understand the critical effects of different motivators of online knowledge sharing.

Secondly, this study contributes to the literature in knowledge sharing and innovation on social media by examining the researchers' online dual knowledge sharing. Although past literature has studied the online knowledge sharing in broad contexts, the study of online knowledge sharing in scientific groups still needs more investigation. Since researchers are the main people who conduct innovation and technology diffusion, the research in this type of group will help researchers concern the importance of inspiring knowledge sharing among scientists and how it happens. Besides, past literature few divides the knowledge into specific types when researchers explore the researchers' online knowledge sharing. This study enriches the literature by discussing the influences of motivations on online implicit knowledge sharing and online explicit knowledge sharing, helping researchers understand the influences of motivations on different types of knowledge sharing.

Thirdly, this study contributes to the literature in researchers' online knowledge sharing context by examining the effects of demographic variables on motivations in knowledge sharing in the online cross-disciplinary research community. Although past literature has tried to explore the researchers' data sharing in the virtual context, not enough papers study influences of demographic variables. The findings in this study show that gender and age are more important in differing attitudes of academia in knowledge sharing. This study enriches the literature by researching behavior in a multi-background research community and revealing the differences in behavior among different groups.

Practitioners can use the results of the study. First, universities and organizations may encourage researchers to join multi-background online communities to inspire people's knowledge sharing. Second, besides enhancing the traditional face-face and mouth-mouth scholarly communication, universities and organizations should concern the importance of establishing the Science 2.0 platform for more possibility of knowledge exchange and innovation.

7.4 Limitations

This research has several limitations. To conduct the survey, the researcher selected the WeChat group "Lao Ta research league" as a focus group. However, since different social media and virtual platforms exist in the markets, only studying one type case may limit the results to extend to other types. While aiming to be more generalizable, further research can compare different social media in the survey when studying researchers' online knowledge sharing behavior. Besides, this research uses a self-reporting method. However, this method may lead to the risk of common method bias. Therefore, further analysis can use other methods to explore sharing behavior and different approaches to collect data. Furthermore, the respondents in this research were Chinese people. Further research should be more extensive in scope.

8. CONCLUSION

Although past literature has proposed many influential factors of the knowledge sharing behavior on social media based on many fundamental theories, not enough research is conducted in researchers' group from the perspective of inter-relationships among influential factors and self-determine theory. This study enriches the gap in the literature on knowledge sharing on social media by proposing a model to investigate the mechanism of how antecedents lead to researchers' online knowledge sharing and community promotion. The online survey data from 301 Chinese researchers were analyzed with SmartPls 2.0 and SPSS PROCESS. Findings provide some implications for future research and practice.

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APPENDIX

Table 12. Demographic information of interviewees

Participant	Gender	Age	Education	Field	Occupation	University type
A	Female	35	Master	Educaiton	Tutor	Oversea
B	Male	40	Doctorate	Art	Lecturer	Domestic
C	Male	29	Doctorate	Archtecture	Researcher	Oversea
D	Female	28	Doctorate	Business	Lecturer	Oversea
E	Female	27	Doctorate	Business	Researcher	Oversea
F	Male	34	Master	Lingusitcs	Lecturer	Domestic
G	Female	26	Master	Business	Researcher	Oversea
H	Male	31	Doctorate	Business	Researcher	Domestic
I	Female	28	Master	Business	Researcher	Oversea
J	Male	37	Doctorate	Art	Lecturer	Domestic

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