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A predictive model of the knowledge-sharing intentions of social Q&A community members: A regression tree approach

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ABSTRACT

Previous research on the factors affecting knowledge sharing has focused on the relationships between a limited number of variables. However, it is unclear how these factors interact with each other and jointly influence knowledge-sharing intentions. Drawing on social cognitive theory (SCT), this paper performs a decision tree analysis to predict the knowledge-sharing intentions of social question-and-answer (Q&A) community members based on a multitude of environmental and individual factors, including a sharing culture, motivations, and individual characteristics. Data from 1,007 users were collected, and a regression tree model was built using the R package *rpart*. The results show that high levels of knowledge-sharing intentions occur among those who strongly enjoyed sharing and who perceived fairness within the community. For those who had a moderate or low level of enjoyment, their willingness to share knowledge was jointly affected by the sharing culture and extrinsic motivations.

1. Introduction

Powered by the continuous growth in and the wide deployment of information and communication technologies, traditional knowledge dissemination methods have undergone tremendous changes. Users are no longer limited to using keyword-based search engines to acquire knowledge; they can now ask questions and seek answers in social question-and-answer (Q&A) communities, where people present their information needs and respond to others' information or knowledge needs on the basis of voluntary participation (Shah et al., 2009). Quora (https://www.quora.com), Zhihu (https://www.zhihu.com), Answers (https://www.answers.com), and Stack Overflow (https://stackoverflow.com) are examples of prevalent social Q&A communities. On the basis of standard Q&A systems, social Q&A communities have incorporated social networking features to facilitate social connections between users (J. Jin et al., 2015). However, similar to the most popular knowledge-sharing platforms, social Q&A communities face severe churn rates (Fang & Zhang, 2019) and sluggish growth in the number of fresh and active users (Song et al., 2019). The main reason for these problems is the scarcity of knowledge sharing among users. Encouraging users to share their knowledge sustainably determines the competitive advantage of online communities, particularly online Q&A communities (Chen, 2007).

Previous studies have explored the factors influencing the intention to share knowledge from the perspective of social cognitive theory (SCT) to tackle the reluctance to share knowledge (e.g., Chen & Hung, 2010; Chou & Hsu, 2018). SCT regards human functioning as the product of a dynamic interplay of individual, behavioral, and environmental influences (Bandura, 1986). For instance, based on SCT, Hsu et al. (2007) introduced a model that includes self-efficacy and outcome expectations as personal sources and multidimensional trusts as environmental stimuli. Although prior studies have expanded our understanding of the individual and environmental factors that affect knowledge sharing (e.g., Chen & Hung, 2010; Kwahk & Park, 2016), it has mostly been restricted to their isolated and direct effects. Wang and Noe (2010) emphasized that prior studies on knowledge sharing have focused more on independent effects and that investigating the relationship between individual and environmental factors based on the perspective of interactional psychology and trait activation is useful for future studies. Similarly, Argote et al. (2003) suggested that the fit between employees and the environment can predict organizational outcomes in knowledge management. Therefore, ignoring the interaction between environmental and individual factors may reduce the external validity of the conclusions of research. To develop a more holistic perspective for motivating knowledge sharing in online communities, the combination of environmental and individual factors must be considered. However, although researchers acknowledge the importance of studying the interaction between environmental and individual factors, there is no empirical research that assesses the combined effects of these two types of factors on users' knowledge-sharing intentions.

This paper aims to address this knowledge gap by answering the following research question: *How do environmental and individual factors interact and jointly influence users' knowledge-sharing intentions in social Q&A communities?* Since SCT emphasizes the importance of both environmental and individual factors, this study explores the interaction effects between environmental factors (sharing culture) and individual factors

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(motivations, personality traits, gender, and age) to explain users' knowledge-sharing intentions from the SCT perspective.

Among the parametric methods used in knowledge-sharing research, linear regression and structural equation modeling are the most common. However, parametric models have difficulty estimating and explaining the complex interactions that occur among three or more variables, and it is also difficult to construct nonlinear models (Giorgi et al., 2016; Strobl et al., 2009). In their attempts to explore variables such as knowledge sharing, studies appear to concentrate on the main effects, considering only a small number of variables at a time. However, a user's knowledge-sharing intentions are affected by multitudinous factors; considering only a limited number of variables may greatly reduce the external validity of the conclusions. Thus, the conclusions drawn from these parametric methods are often explanatory rather than predictive. In the context of the current replication crisis, increasing evidence indicates that numerous findings from empirical studies in the field of psychology cannot be replicated when experiments and data analyses are performed in the future in accordance with the original study procedures (Open Science Collaboration, 2015; Yarkoni & Westfall, 2017). To address this issue, Yarkoni and Westfall (2017) suggested that research projects that focus on prediction and that present explanations as an auxiliary objective might be more advantageous from a longer-term perspective. As a predictive science, machine learning involves important principles and techniques that could profitably be incorporated into psychology (Jacobucci & Grimm, 2020; Yarkoni & Westfall, 2017). In machine learning and data mining, decision trees are one of the most prevalent methods of classification (Guggari et al., 2018). This method employs a group of algorithms to evaluate the variables that optimally predict a target variable by segregating a dataset into progressively smaller subsets that are gradually homogeneous with respect to the outcome attribute (Witten et al., 2011). Decision trees possess the following advantages: First, they are considered to be a nonparametric method that makes no assumptions about the distribution of space (Rokach, 2016). Second, they can handle both categorical and continuous variables in an efficient manner (James et al., 2013). Based on the data type to which the dependent variable belongs, there are classification trees, where the dependent variable can be a discrete value set, and regression trees, where the dependent variable can take continuous values. Third, a decision tree can be visualized and is easy to explain. In the field of psychology, decision trees have been successfully applied to identify smoking cessation attempt probabilities (Yong et al., 2020), assess the risk and protective factors of being bullied among adolescents (Moon et al., 2016), predict employees' perceptions of organizational support (Giorgi et al., 2016), document adult suicidal ideations (Bae, 2019), and assess posttraumatic stress disorders (Stewart et al., 2016). A decision tree identifies the most influential predictor and the way different predictors interact with each other to distinguish groups with respect to the dependent variable (Liu et al., 2011), which coincides with our research purposes. Thus, this study applies decision tree analysis to explore the influence of the interaction of environmental and individual factors on members' intentions to share knowledge.

Our work has theoretical and practical significance. From a theoretical perspective, the proposed model expands our theoretical understanding of environmental and individual factors by looking beyond their independent impacts, and it shows that the person-environment fit matters in users' knowledge sharing. Our study is the first attempt to empirically investigate the impact of person-environment interactions on knowledge sharing. Second, this research enriches our understanding of motivation theory. Regression trees can help researchers identify different behavioral patterns of subgroups of users, providing an opportunity to discover the boundary conditions that animate the different motivational factors that encourage users to share knowledge. As a practical research contribution, this study emphasizes the impact of different combinations of environmental and individual factors on cultivating users' knowledge sharing, which for social Q&A community managers may be informative with regard to the design of personalized solutions that encourage users to share knowledge.

2. Literature review

2.1. Knowledge sharing

Mirzaee and Ghaffari (2018) viewed knowledge sharing as an exchange between a provider and a recipient. In the context of online communities, Yu et al. (2010) defined knowledge sharing as a process involving a sender's effort and completion to transfer knowledge and a recipient's effective absorption of this knowledge. Previous studies have used knowledge-sharing intentions as a reliable and valid indicator of knowledge-sharing behavior (Lin, 2007; So & Bolloju, 2005). Knowledge-sharing intentions are defined as the degree to which an individual is willing to share knowledge (Bock et al., 2005). In our study, knowledge-sharing intentions refer to the degree to which a user may engage in knowledge-sharing activities, such as answering questions or writing articles in social Q&A communities. In the literature, the factors affecting knowledge sharing are typically differentiated into individual and environmental factors.

2.2. Individual factors affecting knowledge sharing

The existing literature contains research on the individual factors affecting users' knowledge sharing in online communities from the perspectives of motivation and individual characteristics (Wang & Noe, 2010; Zeraati et al., 2019). Motivation has been identified as one of the most vital factors of knowledge sharing (Wasko & Faraj, 2005). The motivation to share knowledge is typically split into two kinds: extrinsic and intrinsic (Gong et al., 2017). Extrinsic motivation stems from some desired consequence of performing a task (Osterloh & Frey, 2000), while in the case of intrinsic motivation, people participate in an activity of their own volition for internal pleasure, fun, a sense of accomplishment, or for the challenge of it (Ryan & Deci, 2000). For Lin (2007), organizational rewards and reciprocity were extrinsic motivators of knowledge-sharing behaviors, while enjoyment and knowledge-sharing self-efficacy were prominent intrinsic motivations used to interpret knowledge-sharing behaviors.

This division has been adopted by subsequent research (e.g., Nguyen, Nham, Froese et al., 2019; Zhao et al., 2016). Therefore, this study uses enjoyment and knowledge-sharing self-efficacy as intrinsic motivations and economic rewards and reciprocity as extrinsic motivations.

2.2.1. Intrinsic motivations for knowledge sharing

Enjoyment and knowledge-sharing self-efficacy are two of the most studied intrinsic motivations that affect the intention to share knowledge (Lin, 2007; Zhao et al., 2016). When social Q&A communities were in their infancy, usage was largely maintained by participants' intrinsic motivation (Wasko & Faraj, 2005). Individuals who exchange knowledge with others are believed to be inherently driven by fun and by the satisfaction they obtain from participation (Wasko & Faraj, 2000). Prior research has confirmed that enjoyment has a significant impact on knowledge sharing (Yu et al., 2010). However, Lai and Chen (2014) noted that the influence of enjoyment on knowledge-sharing intentions differs between posters and lurkers. Posters engage in sharing they enjoy doing so, while lurkers cannot feel gratification from helping other members (Fang & Zhang, 2019). Therefore, user characteristics or types may be moderating variables in the relationship between enjoyment and knowledge sharing.

Knowledge-sharing self-efficacy represents an individual's confidence that he or she possesses the abilities and assets needed to offer useful knowledge (Kankanhalli et al., 2005). Bandura's (2006) reciprocal determinism theory assumes that self-efficacy serves a vital function in influencing and encouraging behavior. Knowledge-sharing self-efficacy comes from the freedom, independence, flexibility and autonomy that individuals experience in knowledge-sharing activities (Lai & Chen, 2014). Once answerers pick a question, they are then concerned about whether they have the ability to answer it (Lai & Chen, 2014). People with a high level of knowledge-sharing self-efficacy think that they can support a community in addressing relevant problems or that can have an impact on the community (Y. Zhang et al., 2019), while individuals lacking self-efficacy worry that they might misguide others or offer fruitless messages (Zhang & He, 2016). Previous studies have shown that knowledge-sharing self-efficacy is positively associated with knowledge sharing (Chen & Hung, 2010; Y. Zhang et al., 2019). However, some studies contradict such findings. For example, Cai and Shi (2020) did not find a significant association between knowledge-sharing self-efficacy and users' knowledge-sharing intentions. Moreover, Y. Zhang et al. (2019) argued that individuals with a high degree of self-efficacy, such as experts, adopt a stringent manner toward answers.

2.2.2. Extrinsic motivations for knowledge sharing

With regard to extrinsic motivation, virtual points (Zhao et al., 2016), virtual currency (Krasonikolakis et al., 2014; Liao et al., 2013) and economic rewards (Liou et al., 2016) have been used to externally motivate community members to engage in knowledge-sharing behaviors. For example, Zhihu.com launched a function called paid consultation, which is a feature in the paid Q&A mode. Users can choose to ask a knowledge contributor a question either publicly or privately by paying the contributor using real currency. The results of monetary rewards are noteworthy because such rewards have shown inconsistent effects on knowledge sharing in online communities: positive (Liou et al., 2016), non-significant (Liao et al., 2013) and even negative (Fang & Zhang, 2019). One likely explanation for these incoherent findings is that other factors may intervene in the relationship between economic rewards and knowledge sharing.

Reciprocity, which is another major aspect of extrinsic motivation, refers to the anticipation of rewarded acts (Bock et al., 2005). Wasko and Faraj (2005) defined reciprocity as the extent to which individuals believe that they can gain mutual benefits by sharing knowledge. Potential knowledge contributors in communities can be extrinsically driven by mutual support (Zhao et al., 2016). Social Q&A communities such as Zhihu.com have a function that invites other members in the community to provide answers to questions. When no one answers a question or the user is dissatisfied with the existing answer, they can invite other users to answer. Additionally, the system recommends excellent answerers or identifies active answering users under the topic to which the question belongs, and answerers who accept the invitation can display "thanks for the invitation from ... " on the first line of their answer. Individuals collect valuable knowledge from knowledge providers and are obligated to send equivalent knowledge back to providers (Schulz, 2001). In support of this idea, several previous studies have found evidence of a significant effect of reciprocity on knowledge sharing (X.-L. Jin et al., 2013; Xiong et al., 2018). Nevertheless, some research has shown that knowledge contributions can occur when there is no reciprocity between the two parties (Wasko & Faraj, 2005). Based on user activity data from Zhihu, Guan et al. (2018) found that the number of answers that users received to their questions did not substantially influence their subsequent knowledge-sharing behavior. The inconsistent results suggest that the relationship between reciprocity and knowledge sharing may be contingent on other variables, such as the user type (Fang & Zhang, 2019).

While both extrinsic and intrinsic motivations may stimulate behavior, they may not additively combine to affect behavior. Deci et al. (2001) notes that tangible rewards have a substantial undermining influence on intrinsic motivation. Similarly, Zhao et al. (2016) found that virtual rewards sabotage the effect of enjoyment on knowledge sharing, while reciprocity undermines the effect of self-efficacy on knowledge-sharing attitudes. It can be concluded that the two types of motivation do not affect knowledge sharing independently and that their interaction may have an undermining effect on users' knowledge-sharing intentions. Therefore, it is necessary to explore the boundary conditions of intrinsic and extrinsic motivations that affect users' knowledge-sharing intentions.

2.2.3. Individual characteristics and knowledge sharing

In addition to domain-specific motives, human behavior is generally governed by abstract personality traits (Jadin et al., 2013). Matzler et al. (2008) demonstrated that knowledge sharing is positively influenced by conscientiousness, agreeableness, and openness. However, they did not investigate extraversion and neuroticism for several reasons, such as the relative paucity of research on these two traits and the constraints imposed by the length of data collection instruments. Later, Teh et al. (2011) argued that extraversion and neuroticism are positively associated with attitudes toward knowledge sharing. However, the positive association between extraversion and knowledge sharing was not confirmed by Borges (2013), who stated that extroverted people appear to dominate conversations. Consequently, they might be less receptive to new ideas. Applying diffusion theory and social value orientation, Jadin et al. (2013) found that personality traits predict knowledge sharing in online communities and that the effect was contingent upon individuals' motivation to write. Specifically, trendsetting can increase the probability that individuals will contribution to Wikipedia, while opinion leadership is negatively associated with knowledge sharing. Thus, personality characteristics probably influence the way people interpret and react to environmental stimuli due to their tendency to sense stimuli from a certain perspective (Wang & Noe, 2010).

Individual characteristics such as gender and age might moderate the relationship between motivation and knowledge sharing. For example, Connelly and Kelloway (2003) found that females need a more positive culture of social interaction to be able to actively perceive a knowledge-sharing culture similar to their male peers. Furthermore, a meta-analysis performed by Nguyen, Nham, Froese et al. (2019) demonstrated that the effect of reciprocity on predicting knowledge sharing was stronger for younger participants. For gender, the effect of self-efficacy on knowledge sharing was more prominent among female groups (Nguyen, Nham, Froese et al., 2019). Thus, this study includes users' personality traits, age, and gender as individual factors affecting their intention to share knowledge.

2.3. Environmental factors affecting knowledge sharing

The characteristics of online communities influence users' perceptions of such communities, thus affecting usage time and the amount of user-generated content (Sun et al., 2014). Prior research has found that certain built-in features and characteristics of online communities such as website function design (Kim & Mrotek, 2016) and incentive mechanisms (Jabr et al., 2014) can motivate users to be more committed and attached to a community and its goals. Additionally, culture (Kim et al., 2015) and climate (Cai & Shi, 2020) play a central role in constructing information and communication technology ecosystems. Similarly, Yu et al. (2010) proposed that in a community, a sharing culture is a vital catalyst for knowledge sharing. Recently, research has highlighted the role of environmental factors in forming knowledge sharing (Cai & Shi, 2020). Therefore, it is necessary to consider environmental factors in research on knowledge sharing.

2.3.1. Sharing culture

A sharing culture is defined as a set of user perceptions of the policies, practices, and procedures of an online community, as well as the observations that are encouraged and expected by the community (Cai & Shi, 2020). Bock et al. (2005) were the first to examine the relationship between organizational climate and employees' knowledge-sharing intentions in an organizational context. Based on their work, Yu et al. (2010) explored the impact of a sharing culture, enjoyment from helping, and perceived usefulness on knowledge sharing via weblogs. A systematic review conducted by Charband and Navimipour (2016) showed that online environments may directly or indirectly affect knowledge sharing. This finding was further confirmed by an empirical study showing that community climate has an effect on knowledge-sharing intentions through the chain mediation of knowledge-sharing self-efficacy and outcome expectations (Cai & Shi, 2020). Although researchers have verified the positive association between a sharing culture and knowledge sharing in online communities (e.g., Pi et al., 2013; Yu et al., 2010), the boundary conditions of the relationship between the two constructs remain unknown.

A sharing culture contains three cultural dimensions: fairness, identification and openness (Yu et al., 2010). Fairness reflects users' sense of the degree to which they perceive that they are being treated fairly by the community (Cai & Shi, 2020). Identification refers to a climate in which members have a sense of belonging to their community, while openness reflects a climate in which knowledge flows freely (Yu et al., 2010).

2.3.2. Fairness

The quality of fairness of online communities is closely related to the attitudes and even the behaviors of users toward such communities (Chen & Hung, 2010). In the social Q&A community setting, askers are prone to feeling that they are treated fairly, and they produce more anticipated value if they believe that the output of using the Q&A service is comparable to their inputs (Raban, 2009). Answerers' perception of fairness is likely to stem from their experience of whether the community administrator's rulings on their posts are fair (Cai & Shi, 2020). Prior research (Chiu et al., 2006; Yu et al., 2010) has underscored the important role of fairness in users' online contribution behavior.

2.3.3. Identification

Social identity theory suggests that individuals prefer to identify themselves as members of a given social relation group in which they build their identity within the social environment to which they belong (Tajfel & Turner, 1979). Building on interactive communication around shared interests (Qu & Lee, 2011), social identity is viewed as a critical determinant affecting the willingness to engage in community activities (Guan et al., 2018). If community members sense an appreciable overlap between their beliefs about who they are as individuals and what the community is and stands for, their perceived sense of belonging and attachment to their community are greater (Mousavi et al., 2017). Users who perceive identification toward the community may lessen the hoarding of knowledge from one another caused by competition (Yu et al., 2010), and they may want to participate in actions that enable the community to succeed. Similarly, Hsu and Lin (2008) found that users were willing to blog because of their community identification.

2.3.4. Openness

Technology that appeals to openness is likely to flourish (Weller, 2007), and environments that promote experimentation are thought to be more beneficial for aggregating favorable knowledge-sharing behavior (Hall, 2001). Previous research on organizational learning has suggested that openness allows the members of project teams to partake in new knowledge sharing processes, as it helps them organize their work (Mueller, 2014). When a community promotes knowledge sharing, constructive member interactions and knowledge sharing improve openness (Pi et al., 2013). Furthermore, providing supportive information to community members motivates them to partake in group activities; thus, it helps create a pro-sharing norm, enhancing users' commitment to the community (Sun et al., 2014). Prior research has indicated that openness within a community is an essential factor in determining users' online knowledge sharing (Cai & Shi, 2020; Pi et al., 2013).

Table 1. Demographic information of the respondents.

Demographic variable	Frequency	Percentage (%)
Gender		
Male	537	53.3
Female	470	46.7
Age		
19 years or less	165	16.4
20–24 years	292	29.0
25–29 years	222	22.0
30–34 years	286	28.4
35–39 years	37	3.7
40 years or more	5	0.5
Educational level		
High school	210	20.9
College	208	20.7
University	526	52.2
Master's degree	53	5.3
Doctoral degree	10	1.0
Duration of membership		
6 months or less	194	19.3
6 months-1 year	303	30.1
1–2 years	305	30.3
2–3 years	108	10.7
3 years or more	97	9.6

3. Method

3.1. Data collection

The data were gathered from China's most popular social Q&A community, Zhihu (https://www.zhihu.com), where questions are asked, answered, organized and edited by users. The broad user group provides a valuable data source for academic research (e.g., Cai & Shi, 2020; Fang & Zhang, 2019). The survey was conducted from March 13 to April 12, 2020. Data were collected from 1125 users of Zhihu through the online survey website Wenjuanxing, which is a professional platform for the distribution of questionnaires. Invalid questionnaires were deleted based on the following criteria: 1) Zhihu users were our survey object. Therefore, the first item of the questionnaire was a screening question. Responses that were not from Zhihu were deleted. 2) The respondents provided the same answers to all questions (e.g., all 1s or all 7s). 3) The respondents completed the questionnaire in less than 100 s, as suggested in the previous literature (e.g., Shao & Pan, 2019; L. Zhang et al., 2020). After deleting 118 invalid responses, we finally obtained 1007 valid responses for our analysis, for an effective response rate of 89.51%. Table 1 presents the descriptive characteristics of the participants.

3.2. Measurement

The personality trait measures were calibrated on a scale of 1 (totally disagree) to 6 (fully agree). Such degree words were derived from the original scale (i.e., Zhang et al., 2019). To avoid misinterpreting the authors' meaning, we have retained these terms to describe the degree of agreement. All other measures were calibrated on a scale of 1 (strongly disagree) to 7 (strongly agree). See Table 2 for all the survey items.

3.2.1. Sharing culture

A sharing culture is defined as a set of user perceptions of the policies, practices, and procedures of an online community, as well as the observations that are encouraged and expected by the community (Cai & Shi, 2020), and it was measured using an eleven-item scale adapted from Yu et al. (2010), which includes fairness, identification and openness. Fairness reflects the extent to which users perceive that they are being treated fairly by the community, and three items measured this dimension. The following is a sample item used to measure fairness: "Overall, I feel fairness within this community". Identification represents the extent to which users belong to their community, while openness reflects a climate in which knowledge flows freely (Yu et al., 2010). Four items measured identification, while four items measured openness. The following is a sample item used to measure identification: "When someone criticizes Zhihu, it feels like they are criticizing me". The following is a sample item used to measure openness: "We are continuously encouraged to bring new knowledge into this community". The Cronbach's α values of the fairness, identification, and openness scales were 0.678, 0.645, and 0.744, respectively.

3.2.2. Enjoyment

Enjoyment represents the extent to which users derive pleasure from helping others (Kwahk & Park, 2016). A four-item scale, adapted from Lin (2007) was used to measure enjoyment. The following is a sample item: "Sharing my knowledge with Zhihu members is pleasurable". Cronbach's α was 0.753.

3.2.3. Knowledge-sharing self-efficacy

Knowledge-sharing self-efficacy refers to an individual's confidence that he or she possesses the abilities and assets needed to offer useful knowledge (Kankanhalli et al., 2005), and it was measured using a three-item scale adapted from Chen and Hung (2010). The following is a sample item: "I have confidence in responding or adding comments to answers or articles posted by other Zhihu members". Cronbach's α was 0.656.

Table 2. The measurement items.

Category	Variable	Item	Reference
Sharing culture	Fairness	FA1: Overall, I feel this community is fair.	(Yu et al., 2010)
		FA2: The Zhihu administrator does not show favoritism to anyone.	
		FA3: I think that the administrators of Zhihu deal with the scope of its acceptance properly.	
	Identification	ID1: I am proud to be a member of Zhihu.	
		ID2: When someone praises Zhihu, it feels like a personal compliment.	
		ID3: When I talk about this community, I usually say "we" rather than "they".	
	Openness	OP1: Open communication is a characteristic of the community as a whole.	
		OP2: We are continuously encouraged to bring new knowledge into this community.	
		OP3: Sharing knowledge is encouraged by Zhihu in action and not only in words.	
Intrinsic motivation	Enjoyment	EN1: I enjoy sharing my knowledge with others through Zhihu.	(Lin, 2007)
		EN2: I enjoy helping others by sharing my knowledge through Zhihu.	
		EN3: It feels good to help someone by sharing my knowledge.	
		EN4: Sharing my knowledge with others through Zhihu gives me pleasure.	
	Knowledge-sharing self-efficacy	KSSE1: I have the expertise, experience and insights needed to provide knowledge that is valuable to other members of Zhihu.	(Chen & Hung, 2010)
		KSSE2: I have confidence in responding or adding comments to answers or articles posted by other members of Zhihu.	
		KSSE3: I have confidence in my ability to provide knowledge that other members of Zhihu consider valuable.	
Extrinsic motivation	Economic rewards	ER1: I know how to gain economic rewards in return for my knowledge sharing on Zhihu.	(Fang & Zhang, 2019)
		ER2: I will receive economic rewards in return for my knowledge sharing on Zhihu.	
		ER3: I think highly of the quantity of my fans because it is related to the amount of economic rewards I receive in return for my knowledge sharing on Zhihu.	
	Reciprocity	RE1: When I share knowledge on Zhihu, I believe that my questions will be answered in the future.	(Zhang et al., 2017)
		RE2: I believe that other members I interact with would help me if I was in need.	
		RE3: When I share my knowledge on Zhihu, I expect some other members to respond when I am in need.	
Personality (CBF-PI-15)	Openness to experience	O1: I'm a person who loves to take risks and break the rules.	(Zhang, Wang, et al., 2019)
		O2: I like adventure.	
		O3: I have a spirit of adventure that no one else has.	
	Conscientiousness	C1: I like to plan things from the beginning.	
		C2: I am diligent in my work or study.	
		C3: One of my characteristics is doing things in a logical and orderly manner.	
	Extraversion	E1: I'm bored by parties with lots of people. (reverse coded)	
		E2: I try to avoid parties with lots of people and noisy environments. (reverse coded)	
		E3: I like to go to social and recreational parties.	
	Agreeableness	A1: I think most people are well intentioned.	
		A2: Although there are some frauds in society, I think most people can be trusted.	
		A3: Although there are some bad things in human society (such as war, evil and fraud), I still believe that human nature is generally good.	
	Neuroticism	N1: I often worry about trifles.	
		N2: I often feel disturbed.	
		N3: I always worry that something bad is going to happen.	
Knowledge-sharing intentions		KS1: If I had some knowledge about a topic, I would consider posting it on Zhihu.	(Lai & Chen, 2014)
		KS2: If I had some knowledge regarding a question someone asked on Zhihu, I would share this knowledge with others.	

3.2.4. Economic rewards

Economic rewards refer to the degree to which users believe that they will receive extrinsic incentives for their knowledge sharing. A three-item scale adapted from Fang and Zhang (2019) was used to measure economic rewards. The following is a sample item: "I think highly of the quantity of my fans because it is related to the amount of economic rewards I receive in return for my knowledge sharing on Zhihu". Cronbach's α was 0.642.

3.2.5. Reciprocity

Reciprocity reflects the extent to which individuals believe that they can gain mutual benefits by sharing knowledge (Wasko & Faraj, 2005), and it was measured using a three-item scale adapted from Zhang et al. (2017). The following is a sample item: "I believe that other members whom I interact with would help me if I was in need". Cronbach's α was 0.633.

3.2.6. Personality traits

The Chinese Big Five Personality Inventory 15 (CBF-PI-15), a fifteen-item scale developed by Zhang et al. (2019), was used to measure personality traits. The CBF-PI-15 was developed based on the work of Goldberg (1993), and it has adequate reliability and validity in the Chinese cultural context. Neuroticism represents the tendency to experience distress, such as anxiety and depression (McCrae & John, 1992), while conscientiousness refers to the tendency to be reliable, deliberate, and achievement oriented and to adhere to goal-oriented behavior (Deluga & Masson, 2000). The following is a sample item used to measure neuroticism: "I often worry about trifles". Cronbach's α was 0.664. The following is a sample item used to measure conscientiousness: "I like to plan things from the beginning". Cronbach's α was 0.653. Agreeableness reflects the aspect of interpersonal relations, characterized by caring, altruism, trust and modesty, whereas openness represents the tendency to be imaginative, perceptive, creative and willing to explore new things (McCrae & John, 1992; Szczygiel & Mikolajczak, 2018). The following is a sample item used to measure agreeableness: “I think most people are well intentioned”. Cronbach’s α was 0.647. The following is a sample item used to measure openness: “I’m a person who loves to take risks and break the rules”. Cronbach’s α was 0.744. Extraversion refers to the tendency to be sociable, active, interpersonally warm and in search of stimulation (Deluga & Masson, 2000). The following is a sample item used to measure extroversion: “I try to avoid parties with lots of people and noisy environments”. Cronbach’s α was 0.666.

3.2.7. Knowledge-sharing intentions

Knowledge-sharing intentions refer to the degree to which a user may engage in knowledge-sharing activities, such as answering questions or writing articles in social Q&A communities. A two-item scale adapted from Lai and Chen (2014) was used to measure knowledge-sharing intentions. The following is a sample item: “If I had some knowledge regarding a question someone asked on Zhihu, I would share this knowledge with others”. Cronbach’s α was 0.665.

3.3. Data analysis

The general objective of a decision tree analysis is to find optimal combinations that predict target variables based on large amounts of data, in contrast to conventional methods that set and validate hypotheses.

The data were randomly split into a training set (90%) and a test set (10%). The training set (906 observations) was used to pick the optimal regression tree model, and this model was used on the test set (101 observations) to appraise its performance accuracy.

Utilizing the R package *rpart* (Therneau & Atkinson, 2019), we built a regression tree model to predict knowledge-sharing intentions. After the regression tree was built, the R package *Metrics* (Hamner & Frasco, 2018) was used for the test set to evaluate the regression model. Finally, the relative importance of the variables was measured via the R package *VIP* (Greenwell et al., 2020). Appendix A displays the flowchart of the data analysis process.

4. Results

The correlations between variables can be found in Appendix B. Except for gender, age, educational level and neuroticism, knowledge-sharing intentions were significantly and positively correlated with all of the variables.

4.1. Regression tree analysis

A regression tree of knowledge-sharing intentions is shown in Figure 1. The final model contained 19 nodes and 10 pathways to knowledge-sharing intentions. The decision tree analysis revealed that the most influential predictor of knowledge-sharing intentions was enjoyment, which appears at the top of the tree (i.e., node 1). Continuing on from node 1, the tree divides and searches iteratively for the strongest association between the remaining variables. The bottom of the figure shows the terminal nodes and the distribution of knowledge-sharing intentions for users falling into each of the categories. Based on the level of enjoyment, the entire regression tree could be roughly divided into three parts.

4.1.1. High level of enjoyment

The first part is the pathway when the level of enjoyment is above 6.375, including two pathways: node 1→node 9→node 17→node 19 and node 1→node 9→node 17→node 18. Notably, these two paths trigger the highest intentions of

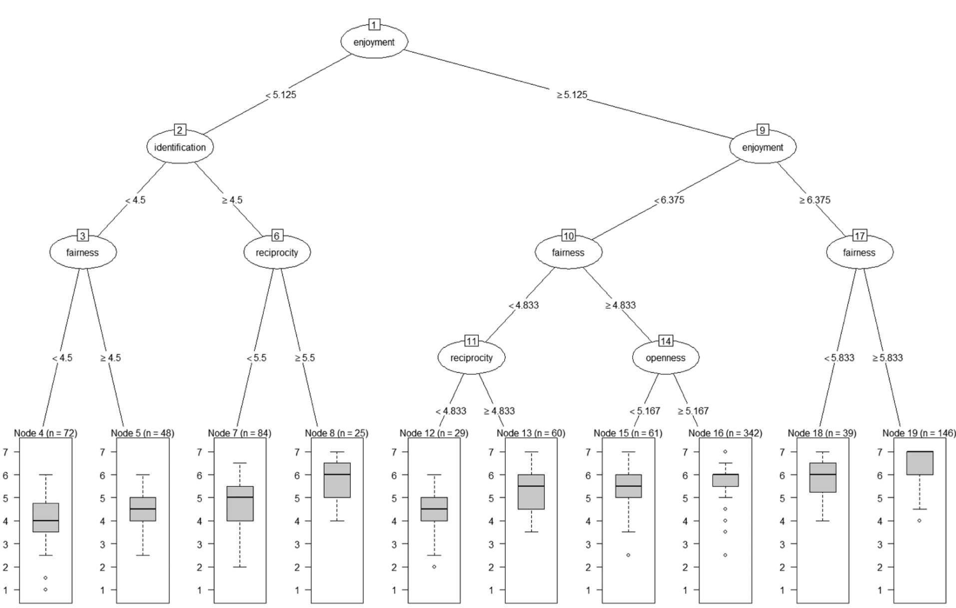

Figure 1. Regression tree predicting knowledge-sharing intentions.

users to share knowledge. Those users who experienced a high degree of enjoyment and perceived fairness had the highest intentions to share (i.e., =6.503). The number of samples involved in this path accounts for 16.11% of the total sample of the training set. For those who reported a high level of enjoyment (i.e., >6.375), even if the perceived fairness score was below 5.833, their knowledge-sharing intentions still maintained a high level (i.e., =5.795).

4.1.2. Moderate level of enjoyment

The second part includes four pathways: node 1→node 9→node 10→node 14→node 16, node 1→node 9→node 10→node 15, node 1→node 9→node 10→node 11→node 13, and node 1→node 9→node 10→node 11→node 12. The level of knowledge-sharing intentions generated by these four pathways successively decreases, among which the fourth pathway (node 1→node 9→node 10→node 11→ node 12) leads to the lowest level of knowledge-sharing intentions. In the group of users who had a moderate level of enjoyment (i.e., 5.125< enjoyment<6.375), knowledge-sharing intentions were mainly affected by fairness, openness, and reciprocity. Among the subgroup that moderately enjoyed sharing knowledge, more users had knowledge-sharing intentions (i.e., =5.768) if they perceived fairness and openness within the community. The number of samples involved in this path accounts for 37.75% of the total sample of the training set, and compared with the other pathways, the proportion of samples composing this pathway is the highest. At this location of the tree (i.e., node 14), users' intentions to share knowledge decreases slightly (i.e., =5.303) if their perceived openness score is below 5.167. On the other side of the tree at node 11, the level of knowledge-sharing intentions decreases to 4.517 for those users who perceived a low degree of fairness (i.e., <4.833) and reciprocity (i.e., <4.833). This pathway leads to a degree of knowledge-sharing intentions that is only slightly higher than that to which the pathway with the lowest knowledge-sharing intentions (i.e., 3.993) leads. This result demonstrats that even if users had a high level of enjoyment but did not perceive fairness within the community and did not expect a high level of reciprocal benefits, their intentions to share knowledge would greatly decline.

4.1.3. Low level of enjoyment

The third part includes four pathways: node 1→node 2→node 6→node 8, node 1→node 2→node 6→node 7, node 1→node 2→node 3→node 4, and node 1→node 2→node 3→node 5. Among those with an enjoyment score of less than a 5.125, identification and reciprocity played a pivotal role in affecting their knowledge-sharing intentions. In the group of users who identified with their community (i.e., an identification score of 4.5 or more), reciprocity determined the upper and lower limits of their intentions to share knowledge. That is, if users expected a high degree of reciprocal benefits (i.e., ≥ 5.5), their intentions to share knowledge would be maintained at a higher level (i.e., =5.700). In contrast, knowledge-sharing intentions would decrease to 4.756 if they perceived a low level of reciprocal benefits (i.e., <5.5). Those who did not have a strong sense of identification with their community (i.e., <4.500) and who did not perceive fairness (i.e., <4.500) were particularly unlikely to share their knowledge (i.e., =3.993).

Overall, particularly high levels of knowledge-sharing intentions occurred among those who strongly enjoyed sharing and who perceived fairness within the community. For users who experienced a moderate level of enjoyment, fairness, openness, and reciprocity were the main predictors. Knowledge-sharing intentions were the lowest among those who had a low level of enjoyment and identification and perceived less fairness.

The test set was used to evaluate the model's performance. First, all the independent variables in the test set were included in the regression tree model generated from the training set to predict knowledge-sharing intentions. Then, we compared the predicted value with the original value of knowledge-sharing intentions in the test set. The root mean square error (*rmse*) was used as a metric for comparing between the predicted value and original value. Finally, the *rmse* obtained was 0.823.

4.2. Relative importance of the variables

A decision tree provides information about the relative importance of different factors affecting users' knowledge-sharing intentions. Figure 2 displays the relative importance of all the independent variables in this study. Enjoyment has the highest relative importance, whereas age has the lowest relative importance. Overall, the relative importance of intrinsic motivation is higher than that of extrinsic motivation. Among extrinsic motivations, the importance of reciprocity is high, while the importance of economic returns is low. The relative importance of a sharing culture is second only to the relative importance of intrinsic motivation, and among the dimensions of a sharing culture, fairness has the highest relative importance. In addition, the relative importance of all five personality traits is generally low.

5. Discussion

Research on the antecedents of knowledge sharing has found many key variables (e.g., Fang & Zhang, 2019; Wang & Noe, 2010). However, methods such as regression analysis and structural equation modeling limit the modeling of the interactions of multiple independent variables (Strobl et al., 2009). As a machine learning method, decision trees can handle complex relationships containing multiple independent variables (Rokach, 2016), which is very helpful in improving the predictive power of such models. This study is the first attempt to apply decision trees to identify the factors that jointly affect users' knowledge-sharing intentions. The established regression tree model extracts five variables (enjoyment, fairness, openness, reciprocity, and identification) from fifteen variables and sorts the sample into 10 subgroups through their interactions.

The regression tree model identified that the root node is enjoyment. This result indicates that among all the independent variables included in this study, enjoyment has the strongest predictive power with respect to knowledge-sharing intentions. In addition, the relative importance of

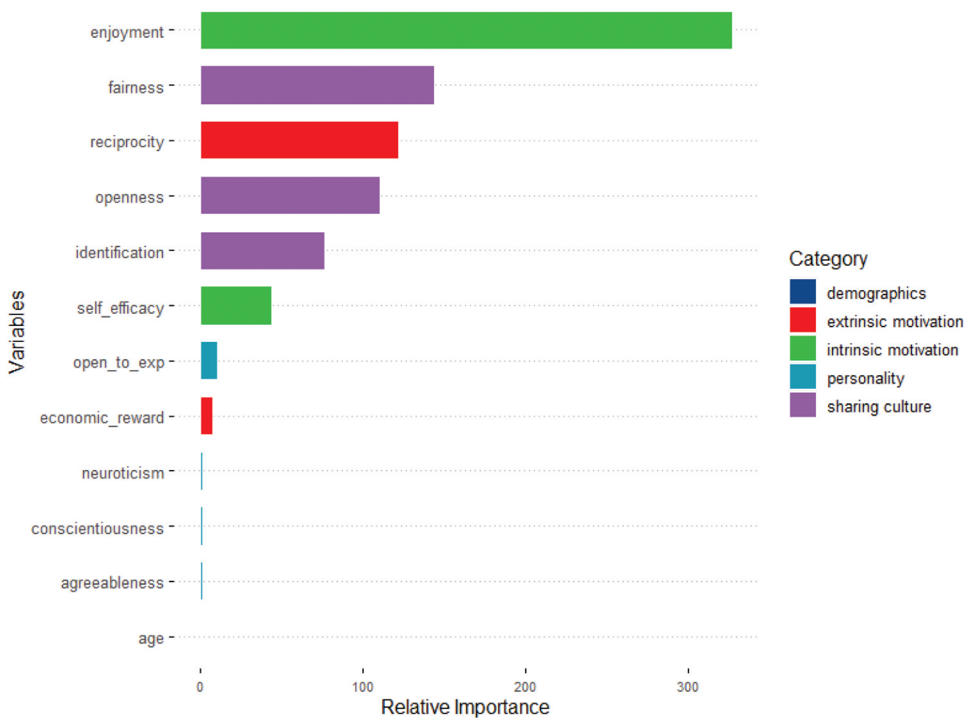

Figure 2. Relative importance of the environmental and individual factors of knowledge-sharing intentions.

intrinsic motivation is higher than that of extrinsic motivation. These findings are consistent with those of Cho et al. (2015) and Nguyen, Nham, Froese et al. (2019). A meta-analysis conducted by Nguyen, Nham, Froese et al. (2019) revealed that both extrinsic and intrinsic motivational factors were related to higher levels of knowledge sharing and that the impact of intrinsic motivation was larger. Cho et al. (2015) found that intrinsic incentives have almost twice the impact on knowledge sharing as extrinsic incentives. Intrinsic motivation is more effective possibly because the enjoyment and satisfaction obtained from the activity itself are long lasting and self-sustaining (Shibchurn & Yan, 2015). Moreover, knowledge sharing is often considered a voluntary behavior (Van den Hooff et al., 2012), and intrinsic motivation is more successful than extrinsic motivation in encouraging voluntary behavior (Almeida et al., 2016).

Each pathway to knowledge-sharing intentions contains either a combination of intrinsic motivation and a sharing culture or a combination of extrinsic motivation and a sharing culture. This result indicates that knowledge sharing is the product of the interaction of environmental factors and motivational factors, which is consistent with the person-environment interaction model of SCT (Bandura, 2001). This finding emphasizes that intrinsic and extrinsic motivations should not always be used simultaneously. When users already have a high level of enjoyment, extra extrinsic motivation will not promote their knowledge-sharing intentions (node 18 and node 19). In other words, communities do not have to provide users who have a high level of enjoyment with more extrinsic incentives; letting them perceive fairness in the community is enough. However, for those with a moderate or low level of enjoyment, as an extrinsic motivation, reciprocity plays a critical role. Perceiving a higher level of reciprocal benefits can increase knowledge-sharing intentions by as much as one unit (node 7 vs. node 8, node 12 vs. node 13). Some online communities have introduced extrinsic incentives to encourage members to contribute, such as gifts, feedback, and social recognition (Tedjamulia et al., 2005). However, extrinsic rewards sometimes undermine intrinsic motivations (Deci et al., 2001; Zhao et al., 2016). This phenomenon is called the motivation crowding effect (Frey & Jegen, 2001). The findings of this study identify the boundary conditions for the interpretation of this effect in online communities. The affordance of intrinsic and extrinsic motivations does not necessarily lead to motivation crowding effects, which depend on the user's level of enjoyment. For high-enjoyment groups, extrinsic motivations may harm knowledge-sharing intentions. However, for those who have a medium or low level of enjoyment, extrinsic incentives can be provided in addition to intrinsic motivations.

As an environmental factor, a sharing culture plays a role in promoting users' knowledge-sharing intentions that cannot be ignored. The three aspects of a sharing culture, i.e., fairness, identification, and openness, all appeared in the regression tree model, which emphasizes the importance of a sharing culture within a community. The findings of Pi et al. (2013) and Yu et al. (2010) support this finding. In both studies, a sharing culture was positively associated with knowledge-sharing intentions. Additionally, since the three aspects of a sharing culture appeared in different paths, different aspects of a sharing culture play different roles for users in different subgroups. For users with a high level of enjoyment, fairness plays a role. For users with a low level of enjoyment, the community should pay more attention to their identification with the community than to fairness.

Most users in the community have a moderate level of enjoyment; thus, the community should focus on their sense of fairness and openness to the community.

Finally, a regression tree provides information about the relative importance of different factors affecting users' intentions to share knowledge. The importance of enjoyment and a sharing culture is relatively high, while the importance of knowledge-sharing self-efficacy, economic rewards and personality traits is relatively low. Knowledge-sharing self-efficacy has shown inconsistent effects on knowledge sharing in the context of online communities: positive (Lin, 2007; Zhang et al., 2017; Y. Zhang et al., 2019) and nonsignificant (Cai & Shi, 2020). This study found that the role of knowledge-sharing self-efficacy is not as important as that of enjoyment, a sharing culture, and reciprocity. In other words, if the community has a favorable sharing culture and users are able to experience enjoyment from sharing knowledge, the function of knowledge-sharing self-efficacy is no longer important. In addition, the relative importance of economic rewards is low, which is consistent with the findings of Deci et al. (2001), who argued that tangible rewards have a substantial undermining effect.

6. Implications and limitations

6.1. Theoretical implications

The impact of environmental factors on online knowledge sharing has been largely neglected by the literature. Although Yu et al. (2010) and Pi et al. (2013) recognized the importance of a sharing culture, they did not further explore the boundary conditions under which such a culture influences knowledge sharing. In addition, there have been inconsistent conclusions regarding the effects of motivation on knowledge sharing (Chung et al., 2016; Nguyen, Nham, Hoang et al., 2019). Our findings provide the basis for a variety of noteworthy theoretical insights.

First, this study leads to a deeper understanding of motivation theories in the field of knowledge sharing by performing a decision tree analysis to construct more holistic relationships between motivation and knowledge-sharing intentions. In addition, we reveal that the role of intrinsic and extrinsic motivations in promoting knowledge-sharing intentions must consider the sharing culture within the community. For users who already have a high level of enjoyment, the mere sense of fairness is enough to propel them to share knowledge. For users with a low level of enjoyment, the role of identification must be considered in addition to the role of fairness. Therefore, the motivational factors of users' knowledge sharing should be understood within the corresponding sharing culture. This research makes substantial contributions to motivation theories and the knowledge management literature by clarifying how environmental factors and motivational factors interact with each other and jointly impact knowledge sharing. Moreover, this study advances the theoretical literature and serves as a reference for future researchers to identify moderating factors covering a spectrum of knowledge-sharing studies.

Second, this study clarifies the boundary conditions of motivation crowding effects (Frey & Jegen, 2001). Previous studies have suggested that extrinsic and intrinsic motivations should not be used together (Deci et al., 2001). Nguyen, Nham, Froese et al. (2019) argued that the interaction between the two forms of motivation has been minimally examined in the area of knowledge sharing. Our findings indicated that motivation causes "crowding" only among users with a very high level of enjoyment. For users with a medium or low level of enjoyment, intrinsic and extrinsic motivations can be used together, but this combination must consider environmental factors such as a sharing culture.

Third, this study determines the relative importance of individual and environmental factors in users' intentions to share knowledge. Although researchers have found that knowledge-sharing self-efficacy (Chen & Hung, 2010; Y. Zhang et al., 2019) and economic rewards (Fang & Zhang, 2019) can affect knowledge sharing, the results of this study demonstrate that the role of knowledge-sharing self-efficacy and economic rewards is masked in the presence of enjoyment and a sharing culture. Therefore, this study argues that among the factors that promote knowledge sharing, enjoyment and a sharing culture should be prioritized, at least for social Q&A communities.

6.2. Practical implications

For Q&A community practitioners, this study provides insights into ways to encourage knowledge sharing among users.

First, this paper emphasizes the importance of enjoyment. Online community managers should attempt to cultivate the enjoyment of users and simultaneously customize various plans that affect their knowledge-sharing intentions based on users' different levels of enjoyment. For users with a high level of enjoyment, managers need to pay attention to only the impact of community fairness. Most users in the community have a moderate level of enjoyment; thus, managers can foster a climate characterized by fairness and openness and offer extrinsic incentives to encourage users to share knowledge. Finally, for users with a low level of enjoyment, the community can cultivate their sense of identification with the community and provide extrinsic incentives as an extra stimulant.

Second, managers can learn from the relative importance of the factors contained in this research to improve their existing incentive strategies. Our results indicate that the relative importance of intrinsic motivation is higher than that of extrinsic motivation, and the relative importance of a sharing culture is second only to the relative importance of intrinsic motivation. Thus, the community should make intrinsic motivations a priority and put a sharing culture, characterized by fairness, identification and openness, on the agenda. Among extrinsic motivations, the importance of reciprocity is much higher than that of economic returns. Thus, the use of extrinsic incentives must consider the size of the user's original level of intrinsic motivation, and reciprocal benefits should be prioritized over the economic incentive policy.

Third, social Q&A communities should also note that the meaning or importance of the different aspects of a sharing culture to different users may vary greatly. In the regression tree model, fairness occurs three times, while identification and openness occur once. Regardless of the user's level of enjoyment, fairness appears in a certain node of these branches. This result indicates that regardless of the type of user, users value the fairness of the community. Thus, the community should pay attention to the function played by community administrators because their review of questions and answers may largely affect users' perceptions of community fairness (Cai & Shi, 2020). In addition, although openness appears only once in the regression tree, its path contains 37.75% of the training sample. Therefore, the role of openness cannot be ignored. Finally, for users belonging to the low-enjoyment subgroup, the role of identification determines the upper and lower limits of these users' knowledge-sharing intentions. Therefore, even if users' original level of enjoyment is not high, the community should pay special attention to cultivating such users' identification with the community.

6.3. Limitations and future directions

First, our research samples were limited to a specific social Q&A community. Because the climate and culture of different communities vary, the findings of this study are not necessarily generalizable to other types of online communities. Although the social Q&A community that we selected for this study is representative, some differences exist between it and other online communities. Future research should include data from other social Q&A communities such as Quora and social networks such as Facebook groups where users come together around a variety of topics to discuss issues and exchange related content to address the issues. Second, different social Q&A communities may have variations in policies with respect to the rewards given to participants who receive high scores by sharing knowledge with others (Kang et al., 2011). The economic reward policy of the community not only affects users' attitudes toward the community (Fang & Zhang, 2019) but also interacts with intrinsic motivations such as enjoyment from helping others, thereby negatively affecting users' attitudes toward knowledge sharing (Zhao et al., 2016). Therefore, caution is required when interpreting our findings. Further examining the robustness of our model in different environments is warranted. Third, representative variables of a sharing culture, motivation and individual characteristics were selected and included in our regression tree model. However, there are more factors that influence users' knowledge sharing. Future research can incorporate more factors to study the effect of multifactor interactions on knowledge sharing.

7. Conclusion

This study employed SCT to explore the joint effects of environmental and individual factors on users' knowledge-sharing intentions in a social Q&A community. The results of the regression tree model demonstrated that enjoyment is the most influential factor predicting users' intentions to share knowledge. At different levels of enjoyment, various aspects of a sharing culture and motivational factors jointly influence knowledge-sharing intentions. For users who experience enjoyment from sharing knowledge, only fairness affects their intentions to share knowledge, and their participation is not dependent on extrinsic incentives. For users who experience a moderate level of enjoyment, both fairness and openness affect their knowledge-sharing intentions, while a low level of reciprocity leads to a substantial reduction in users' intentions to share knowledge. Finally, for users who experience a low level of enjoyment, their knowledge-sharing intentions are affected by identification and fairness, while a high level of reciprocity greatly increases their knowledge-sharing intentions.

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References

Almeida, F. C. D., Lesca, H., & Canton, A. W. P. (2016). Intrinsic motivation for knowledge sharing – competitive intelligence process in a telecom company. *Journal of Knowledge Management*, *20*(6), 1282–1301. https://doi.org/10.1108/JKM-02-2016-0083

Argote, L., McEvily, B., & Reagans, R. (2003). Managing knowledge in organizations: An integrative framework and review of emerging themes. *Management Science*, *49*(4), 571–582. https://doi.org/10.1287/mnsc.49.4.571.14424

Bae, S.-M. (2019). The prediction model of suicidal thoughts in Korean adults using decision tree analysis: A nationwide cross-sectional study. *PLoS One*, *14*(10), e0223220. https://doi.org/https://doi.org/https://doi.org/10.1371/journal.pone.0223220

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*(1), 1–26. https://doi.org/10.1146/annurev.psych.52.1.1

Bandura, A. (2006). Toward a psychology of human agency. *Perspectives on Psychological Science*, *1*(2), 164–180. https://doi.org/10.1111/j.1745-6916.2006.00011.x

Bock, G. W., Zmud, R. W., Kim, Y. G., & Lee, J. N. (2005). Behavioral intention formation in knowledge sharing: Examining the roles of extrinsic motivators, social-psychological forces, and organizational climate. *Mis Quarterly*, *29*(1), 87–111. https://doi.org/10.2307/25148669

Borges, R. (2013). Tacit knowledge sharing between IT workers: The role of organizational culture, personality, and social environment. *Management Research Review*, *36*(1), 89–108. https://doi.org/10.1108/01409171311284602

Cai, Y., & Shi, W. (2020). The influence of the community climate on users' knowledge-sharing intention: The social cognitive theory perspective. *Behaviour & Information Technology*, 1–17. https://doi.org/10.1080/0144929X.2020.1808704

Charband, Y., & Navimipour, N. J. (2016). Online knowledge sharing mechanisms: A systematic review of the state of the art literature and recommendations for future research. *Information Systems Frontiers*, *18*(6), 1131–1151. https://doi.org/10.1007/s10796-016-9628-z

Chen, C.-J., & Hung, S.-W. (2010). To give or to receive? Factors influencing members' knowledge sharing and community promotion in professional virtual communities. *Information & Management*, *47*(4), 226–236. https://doi.org/10.1016/j.im.2010.03.001

Chen, I. Y. (2007). The factors influencing members' continuance intentions in professional virtual communities—A longitudinal study.

Journal of Information Science, 33(4), 451–467. https://doi.org/10.1177/0165551506075323

Chiu, C.-M., Hsu, M.-H., & Wang, E. T. G. (2006). Understanding knowledge sharing in virtual communities: An integration of social capital and social cognitive theories. *Decision Support Systems*, *42*(3), 1872–1888. https://doi.org/10.1016/j.dss.2006.04.001

Cho, I., Park, H., & Kim, J. K. (2015). The relationship between motivation and information sharing about products and services on Facebook. *Behaviour & Information Technology*, *34*(9), 858–868. https://doi.org/10.1080/0144929X.2014.988177

Chou, S.-W., & Hsu, C.-S. (2018). An empirical investigation on knowledge use in virtual communities–A relationship development perspective. *International Journal of Information Management*, *38*(1), 243–255. https://doi.org/10.1016/j.ijinfomgt.2017.10.003

Chung, N., Nam, K., & Koo, C. (2016). Examining information sharing in social networking communities: Applying theories of social capital and attachment. *Telematics and Informatics*, *33*(1), 77–91. https://doi.org/10.1016/j.tele.2015.05.005

Connelly, C., . E., & Kelloway, E. K. (2003). Predictors of employees' perceptions of knowledge sharing cultures. *Leadership & Organization Development Journal*, *24*(5), 294–301. https://doi.org/10.1108/01437730310485815

Deci, E. L., Koestner, R., & Ryan, R. M. (2001). Extrinsic rewards and intrinsic motivation in education: Reconsidered once again. *Review of Educational Research*, *71*(1), 1–27. https://doi.org/10.3102/00346543071001001

Deluga, R. J., & Masson, S. (2000). Relationship of resident assistant conscientiousness, extraversion, and positive affect with rated performance. *Journal of Research in Personality*, *34*(2), 225–235. https://doi.org/10.1006/jrpe.1999.2272

Fang, C., & Zhang, J. (2019). Users' continued participation behavior in social Q&A communities: A motivation perspective. *Computers in Human Behavior*, *92*, 87–109. https://doi.org/10.1016/j.chb.2018.10.036

Frey, B. S., & Jegen, R. (2001). Motivation crowding theory. *Journal of Economic Surveys*, *15*(5), 589–611. https://doi.org/10.1111/1467-6419.00150

Giorgi, G., Dubin, D., & Perez, J. F. (2016). Perceived organizational support for enhancing welfare at work: A regression tree model. *Frontiers in Psychology*, *7*, 1770. https://doi.org/10.3389/fpsyg.2016.01770

Goldberg, L. R. (1993). The structure of phenotypic personality traits. *American Psychologist*, *48*(1), 26–34. https://doi.org/10.1037/0003-066X.48.1.26

Gong, Y., Wu, J., song, L. J., & Zhang, Z. (2017). Dual tuning in creative processes: Joint contributions of intrinsic and extrinsic motivational orientations. *Journal of Applied Psychology*, *102*(5), 829–844. https://doi.org/10.1037/apl0000185

Greenwell, B. M., & Boehmke, B. C. (2020). Variable Importance Plots—An Introduction to the vip Package. *The R Journal*,*12*(1), 343–366.

Guan, T., Wang, L., Jin, J., & Song, X. (2018). Knowledge contribution behavior in online Q&A communities: An empirical investigation. *Computers in Human Behavior*, *81*, 137–147. https://doi.org/10.1016/j.chb.2017.12.023

Guggari, S., Kadappa, V., & Umadevi, V. (2018). Non-sequential partitioning approaches to decision tree classifier. *Future Computing and Informatics Journal*, *3*(2), 275–285. https://doi.org/10.1016/j.fcij.2018.06.003

Hall, H. (2001). Input-friendliness: Motivating knowledge sharing across intranets. *Journal of Information Science*, *27*(3), 139–146. https://doi.org/10.1177/016555150102700303

Hamner, B., & Frasco, M. (2018). *Metrics: Evaluation metrics for machine learning*. R package version 0.1.4. https://CRAN.R-project.org/package=Metrics

Hsu, C.-L., & Lin, J.-C.-C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management*, *45*(1), 65–74. https://doi.org/10.1016/j.im.2007.11.001

Hsu, M.-H., Ju, T. L., Yen, C.-H., & Chang, C.-M. (2007). Knowledge sharing behavior in virtual communities: The relationship between trust, self-efficacy, and outcome expectations. *International Journal of Human-Computer Studies*, *65*(2), 153–169. https://doi.org/10.1016/j.ijhcs.2006.09.003

Jabr, W., Mookerjee, R., Tan, Y., & Mookerjee, V. (2014). Leveraging philanthropic behavior for customer support: The case of user support forums. *Mis Quarterly*, *38*(1), 187–208. https://doi.org/10.25300/misq/2014/38.1.09

Jacobucci, R., & Grimm, K. J. (2020). Machine learning and psychological research: The unexplored effect of measurement. *Perspective on Psychological Science*, *15*(3), 809–816. https://doi.org/10.1177/1745691620902467

Jadin, T., Gnambs, T., & Batinic, B. (2013). Personality traits and knowledge sharing in online communities. *Computers in Human Behavior*, *29*(1), 210–216. https://doi.org/10.1016/j.chb.2012.08.007

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). Tree-based methods. In G. James, D. Witten, T. Hastie, & R. Tibshirani (Eds.), *An introduction to statistical learning: With applications in R* (pp. 303–335). Springer. https://doi.org/10.1007/978-1-4614-7138-7_8

Jin, J., Li, Y., Zhong, X., & Zhai, L. (2015). Why users contribute knowledge to online communities: An empirical study of an online social Q&A community. *Information & Management*, *52*(7), 840–849. https://doi.org/10.1016/j.im.2015.07.005

Jin, X.-L., Zhou, Z., Lee, M. K. O., & Cheung, C. M. K. (2013). Why users keep answering questions in online question answering communities: A theoretical and empirical investigation. *International Journal of Information Management*, *33*(1), 93–104. https://doi.org/10.1016/j.ijinfomgt.2012.07.007

Kang, M., Kim, B., Gloor, P., & Bock, G.-W. (2011). Understanding the effect of social networks on user behaviors in community-driven knowledge services. *Journal of the American Society for Information Science and Technology*, *62*(6), 1066–1074. https://doi.org/10.1002/asi.21533

Kankanhalli, A., Tan, B., & Wei, K. K. (2005). Contributing knowledge to electronic knowledge repositories: An empirical investigation. *Mis Quarterly*, *29*(1), 113–143. https://doi.org/10.2307/25148670

Kim, H., Shin, D.-H., & Lee, D. (2015). A socio-technical analysis of software policy in Korea: Towards a central role for building ICT ecosystems. *Telecommunications Policy*, *39*(11), 944–956. https://doi.org/10.1016/j.telpol.2015.09.001

Kim, H.-S., & Mrotek, A. (2016). A functional and structural diagnosis of online health communities sustainability: A focus on resource richness and site design features. *Computers in Human Behavior*, *63*, 362–372. https://doi.org/10.1016/j.chb.2016.05.004

Krasonikolakis, I., Vrechopoulos, A., & Pouloudi, A. (2014). Store selection criteria and sales prediction in virtual worlds. *Information & Management*, *51*(6), 641–652. https://doi.org/10.1016/j.im.2014.05.017

Kwahk, K.-Y., & Park, D.-H. (2016). The effects of network sharing on knowledge-sharing activities and job performance in enterprise social media environments. *Computers in Human Behavior*, *55*, 826–839. https://doi.org/10.1016/j.chb.2015.09.044

Lai, H.-M., & Chen, T. T. (2014). Knowledge sharing in interest online communities: A comparison of posters and lurkers. *Computers in Human Behavior*, *35*, 295–306. https://doi.org/10.1016/j.chb.2014.02.004

Liao, C., To, P.-L., & Hsu, F.-C. (2013). Exploring knowledge sharing in virtual communities. *Online Information Review*, *37*(6), 891–909. https://doi.org/10.1108/OIR-11-2012-0196

Lin, H.-F. (2007). Effects of extrinsic and intrinsic motivation on employee knowledge sharing intentions. *Journal of Information Science*, *33*(2), 135–149. https://doi.org/10.1177/0165551506068174

Liou, D.-K., Chih, W.-H., Yuan, C.-Y., & Lin, C.-Y. (2016). The study of the antecedents of knowledge sharing behavior: The empirical study of Yambol online test community. *Internet Research*, *26*(4), 845–868. https://doi.org/10.1108/IntR-10-2014-0256

Liu, Y. Y., Yang, M., Ramsay, M., Li, X. S., & Coid, J. W. (2011). A comparison of logistic regression, classification and regression tree, and neural networks models in predicting violent re-offending. *Journal of Quantitative Criminology*, *27*(4), 547–573. https://doi.org/10.1007/s10940-011-9137-7

Matzler, K., Renzl, B., Müller, J., Herting, S., & Mooradian, T. A. (2008). Personality traits and knowledge sharing. *Journal of Economic Psychology*, *29*(3), 301–313. https://doi.org/10.1016/j.joep.2007.06.004

McCrae, R. R., & John, O. P. (1992). An Introduction to the Five-Factor Model and Its Applications. *Journal of Personality*, *60*(2), 175–215. https://doi.org/10.1111/j.1467-6494.1992.tb00970.x
Mirzaee, S., & Ghaffari, A. (2018). Investigating the impact of information systems on knowledge sharing. *Journal of Knowledge Management*, *22*(3), 501–520. https://doi.org/10.1108/JKM-08-2017-0371
Moon, S. S., Kim, H., Seay, K., Small, E., & Kim, Y. K. (2016). Ecological factors of being bullied among adolescents: A classification and regression tree approach. *Child Indicators Research*, *9*(3), 743–756. https://doi.org/10.1007/s12187-015-9343-1
Mousavi, S., Roper, S., & Keeling, K. A. (2017). Interpreting social identity in online brand communities: Considering posters and lurkers. *Psychology & Marketing*, *34*(4), 376–393. https://doi.org/10.1002/mar.20995
Mueller, J. (2014). A specific knowledge culture: Cultural antecedents for knowledge sharing between project teams. *European Management Journal*, *32*(2), 190–202. https://doi.org/10.1016/j.emj.2013.05.006
Nguyen, T.-M., Nham, T. P., Froese, F. J., & Malik, A. (2019). Motivation and knowledge sharing: A meta-analysis of main and moderating effects. *Journal of Knowledge Management*, *23*(5), 998–1016. https://doi.org/10.1108/JKM-01-2019-0029
Nguyen, T.-M., Nham, T. P., & Hoang, V.-N. (2019). The theory of planned behavior and knowledge sharing: A systematic review and meta-analytic structural equation modelling. *VINE Journal of Information and Knowledge Management Systems*, *49*(1), 76–94. https://doi.org/10.1108/VJIKMS-10-2018-0086
Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716. https://doi.org/10.1126/science.aac4716
Osterloh, M., & Frey, B. S. (2000). Motivation, knowledge transfer, and organizational forms. *Organization Science*, *11*(5), 538–550. https://doi.org/10.1287/orsc.11.5.538.15204
Pi, S.-M., Chou, C.-H., & Liao, H.-L. (2013). A study of Facebook Groups members' knowledge sharing. *Computers in Human Behavior*, *29*(5), 1971–1979. https://doi.org/10.1016/j.chb.2013.04.019
Qu, H., & Lee, H. (2011). Travelers' social identification and membership behaviors in online travel community. *Tourism Management*, *32*(6), 1262–1270. https://doi.org/10.1016/j.tourman.2010.12.002
Raban, D. R. (2009). Self-presentation and the value of information in Q&A websites. *Journal of the American Society for Information Science and Technology*, *60*(12), 2465–2473. https://doi.org/10.1002/asi.21188
Rokach, L. (2016). Decision forest: Twenty years of research. *Information Fusion*, *27*, 111–125. https://doi.org/10.1016/j.inffus.2015.06.005
Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, *25*(1), 54–67. https://doi.org/10.1006/ceps.1999.1020
Schulz, M. (2001). The uncertain relevance of newness: Organizational learning and knowledge flows. *The Academy of Management Journal*, *44*(4), 661–681. https://doi.org/10.5465/3069409
Shah, C., Oh, S., & Oh, J. S. (2009). Research agenda for social Q&A. *Library & Information Science Research*, *31*(4), 205–209. https://doi.org/10.1016/j.lisr.2009.07.006
Shao, Z., & Pan, Z. (2019). Building Guanxi network in the mobile social platform: A social capital perspective. *International Journal of Information Management*, *44*, 109–120. https://doi.org/10.1016/j.ijinfomgt.2018.10.002
Shibchurn, J., & Yan, X. (2015). Information disclosure on social networking sites: An intrinsic–extrinsic motivation perspective. *Computers in Human Behavior*, *44*, 103–117. https://doi.org/10.1016/j.chb.2014.10.059
So, J., & Bolloju, N. (2005). Explaining the intentions to share and reuse knowledge in the context of IT service operations. *Journal of Knowledge Management*, *9*(6), 30–41. https://doi.org/10.1108/13673270510629945
Song, Z., Dong, Q., Cao, G., & Chen, Y. (2019). What will influence users' knowledge sharing behavior in the social Q&A community? *Proceedings of the Association for Information Science and Technology*, *56*(1), 762–764. https://doi.org/10.1002/pra2.164
Stewart, R. W., Tuerk, P. W., Metzger, I. W., Davidson, T. M., & Young, J. (2016). A decision-tree approach to the assessment of posttraumatic stress disorder: Engineering empirically rigorous and ecologically valid assessment measures. *Psychological Services*, *13*(1), 1–9. https://doi.org/10.1037/ser0000069
Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, *14*(4), 248–323. https://doi.org/10.1037/a0016973
Sun, N., Rau, P. P.-L., & Ma, L. (2014). Understanding lurkers in online communities: A literature review. *Computers in Human Behavior*, *38*, 110–117. https://doi.org/10.1016/j.chb.2014.05.022
Szczygiel, D., & Mikolajczak, M. (2018). Is it enough to be an extrovert to be liked? Emotional competence moderates the relationship between extraversion and peer-rated likeability. *Frontiers in Psychology*, *9*(804). https://doi.org/10.3389/fpsyg.2018.00804
Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. In W. Austin & S. Worchel (Eds.), *The social psychology of intergroup relations* (pp. 33–47). Brooks/Cole. https://doi.org/10.4324/9780203505984-16
Tedjamulia, S. J. J., Dean, D. L., Olsen, D. R., & Albrecht, C. C. (2005, 6 January). Motivating content contributions to online communities: Toward a more comprehensive theory. *The 38th Annual Hawaii International Conference on System Sciences*, Big Island, HI, USA.
Teh, P.-L., Yong, -C.-C., Chong, C.-W., & Yew, S.-Y. (2011). Do the big five personality factors affect knowledge sharing behaviour? A study of Malaysian universities. *Malaysian Journal of Library & Information Science*, *16*(1), 47–62. https://mjlis.um.edu.my/article/view/6682
Therneau, T., & Atkinson, B. (2019). *Rpart: Recursive partitioning and regression trees*. R package version 4.1-15. https://CRAN.R-project.org/package=rpart
van den Hooff, B., Schouten, A. P., & Simonovski, S. (2012). What one feels and what one knows: The influence of emotions on attitudes and intentions towards knowledge sharing. *Journal of Knowledge Management*, *16*(1), 148–158. https://doi.org/10.1108/13673271211198990
Wang, S., & Noe, R. A. (2010). Knowledge sharing: A review and directions for future research. *Human Resource Management Review*, *20*(2), 115–131. https://doi.org/10.1016/j.hrmr.2009.10.001
Wasko, M. L., & Faraj, S. (2000). "It is what one does": Why people participate and help others in electronic communities of practice. *Journal of Strategic Information Systems*, *9*(2), 155–173. https://doi.org/10.1016/S0963-8687(00)00045-7
Wasko, M. L., & Faraj, S. (2005). Why should I share? Examining social capital and knowledge contribution in electronic networks of practice. *Mis Quarterly*, *29*(1), 35–57. https://doi.org/10.2307/25148667
Weller, M. (2007). The distance from isolation: Why communities are the logical conclusion in e-learning. *Computers & Education*, *49*(2), 148–159. https://doi.org/10.1016/j.compedu.2005.04.015
Witten, I. H., Frank, E., & Hall, M. A. (2011). *Data mining: Practical machine learning tools and techniques* (3rd ed.). Morgan Kaufmann.
Xiong, Y., Cheng, Z., Liang, E., & Wu, Y. (2018). Accumulation mechanism of opinion leaders' social interaction ties in virtual communities: Empirical evidence from China. *Computers in Human Behavior*, *82*, 81–93. https://doi.org/10.1016/j.chb.2018.01.005
Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, *12*(6), 1100–1122. https://doi.org/10.1177/1745691617693393
Yong, -H.-H., Karmakar, C., Borland, R., Kusmakar, S., Fuller-Tyszkiewicz, M., & Yearwood, J. (2020). Identifying smoker subgroups with high versus low smoking cessation attempt probability: A decision tree analysis approach. *Addictive Behaviors*, *103*, 106258. https://doi.org/10.1016/j.addbeh.2019.106258
Yu, T.-K., Lu, L.-C., & Liu, T.-F. (2010). Exploring factors that influence knowledge sharing behavior via weblogs. *Computers in Human Behavior*, *26*(1), 32–41. https://doi.org/10.1016/j.chb.2009.08.002
Zeraati, H., Rajabion, L., Molavi, H., & Navimipour, N. J. (2019). A model for examining the effect of knowledge sharing and new IT-based technologies on the success of the supply chain management systems. *Kybernetes*, *49*(2), 229–251. https://doi.org/10.1108/K-06-2018-0280
Zhang, L., & He, J. (2016). Critical factors affecting tacit-knowledge sharing within the integrated project team. *Journal of Management*

in Engineering, *32*(2), 04015045. https://doi.org/10.1061/(ASCE)ME.1943-5479.0000402

Zhang, L., Shao, Z., Li, X., & Feng, Y. (2020). Gamification and online impulse buying: The moderating effect of gender and age. *International Journal of Information Management*, 102267. https://doi.org/10.1016/j.ijinfomgt.2020.102267

Zhang, X., Liu, S., Deng, Z., & Chen, X. (2017). Knowledge sharing motivations in online health communities: A comparative study of health professionals and normal users. *Computers in Human Behavior*, *75*, 797–810. https://doi.org/10.1016/j.chb.2017.06.028

Zhang, X., Wang, M.-C., He, L., Jie, L., & Deng, J. (2019). The development and psychometric evaluation of the Chinese big five personality inventory-15. *PLoS One*, *14*(8), 1–21. https://doi.org/10.1371/journal.pone.0221621

Zhang, Y., Zhang, M., Luo, N., Wang, Y., & Niu, T. (2019). Understanding the formation mechanism of high-quality knowledge in social question and answer communities: A knowledge co-creation perspective. *International Journal of Information Management*, *48*, 72–84. https://doi.org/10.1016/j.ijinfomgt.2019.01.022

Zhao, L., Detlor, B., & Connelly, C. E. (2016). Sharing knowledge in social Q&A sites: The unintended consequences of extrinsic motivation. *Journal of Management Information Systems*, *33*(1), 70–100. https://doi.org/10.1080/07421222.2016.1172459

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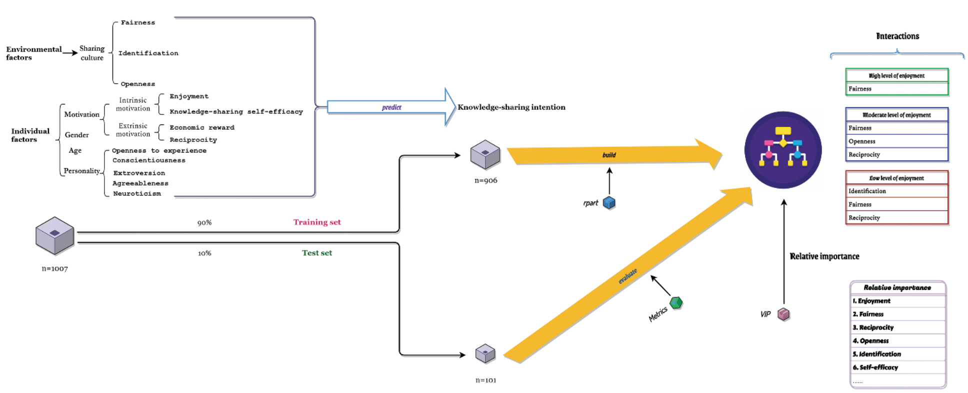
Appendix A.



Appendix B. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. gender	–																
2. age	−0.638***	–															
3. edu	−0.170***	0.358***	–														
4. mem	−0.188***	0.313***	0.321***	–													
5. O	−0.031	−0.009	−0.011	0.077*	–												
6. C	0.007	0.049	0.107***	0.137***	0.394***	–											
7. E	0.095**	−0.043	−0.045	0.012	0.198***	0.121***	–										
8. A	−0.012	0.081**	0.106***	0.151***	0.189***	0.323***	0.100**	–									
9. N	0.023	−0.036	−0.051	−0.077*	−0.105***	−0.058	−0.286***	−0.020	–								
10. ID	−0.012	0.035	−0.022	0.081**	0.251***	0.266***	0.126***	0.322***	0.034	–							
11. OP	0.008	0.017	0.039	0.145***	0.151***	0.280***	0.091**	0.400***	0.053	0.551***	–						
12. FA	0.002	0.024	−0.000	0.068*	0.139***	0.240***	0.111***	0.375***	0.062	0.629***	0.578***	–					
13. EN	−0.004	0.078*	0.041	0.144***	0.171***	0.290***	0.121***	0.437***	0.023	0.605***	0.693***	0.655***	–				
14. KSSE	−0.066*	0.069*	0.035	0.109***	0.262***	0.302***	0.136***	0.315***	0.030	0.524***	0.492***	0.480***	0.494***	–			
15. ER	−0.061	0.045	−0.013	0.013	0.205***	0.229***	0.044	0.081**	0.102**	0.289***	0.173***	0.197***	0.128***	0.365***	–		
16. RE	−0.001	0.049	0.035	0.105***	0.128***	0.248***	0.090**	0.419***	0.086**	0.518***	0.620***	0.597***	0.644***	0.529***	0.161***	–	
17. KS	−0.010	0.044	0.05	0.13***	0.134***	0.223***	0.085**	0.346***	0.027	0.524***	0.536***	0.563***	0.615***	0.488***	0.159***	0.551***	–

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$. edu = education; mem = membership; O = openness to experience; C = conscientiousness; E = extroversion; A = agreeableness; N = neuroticism; ID = identification; OP = openness; FA = fairness; EN = enjoyment; KSSE = knowledge-sharing self-efficacy; ER = economic rewards; RE = reciprocity; KS = knowledge-sharing intentions