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Why do People Share? Main Motives of Sharing Intention in Virtual Communities.

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Statement of Originality

This document is written by Alejandro Esteban Argüello Ordoñez, who declares to take full responsibility for the contents of this document.

I declare that the text and the work presented in this document is original and that no sources other than those mentioned in the text and its references have been used in creating it.

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Introduction

According to the Digital Media Research Group (2012) which is part of the Market Intelligence & Consulting Institute (MIC) and was established in 1987 as a division of Taiwan's Institute for Information Industry, more than 50 percent of online consumers change their purchasing decisions given the information provided in virtual communities or blogs while shopping (cited in Liao, To, & Hsu, 2013). Virtual communities (VCs) are groups of people with common interests and practices that communicate regularly in an organized way over a common communication medium like a bulletin board, in which users can post their comments and reviews (Arinze, Gefen & Ridings, 2002). These communities bring people together, allowing them to share information moved by different causes. This results in an exchange of knowledge that will benefit the parties involved (Chen, Chang, & Liu, 2012), for example Tripadvisor and Taringa[1]. In this case, Tripadvisor is going to be considered. Tripadvisor is an online community created in February 2000, in the United States. It is one of the biggest travel sites with more than 200 million members.

Even though the amount of people searching for information online is growing[2], only a small part of these people take the initiative to share knowledge in said virtual communities. Taking this into account, there are differences between people that share and don't share. For understanding this difference it is important to first study the intentions that drive this behavior. Enjoy in helping, reciprocity, reputation, self-efficacy, and self-esteem, where chosen from the literature and tested to find out if they had a significant effect towards the intention to share, and also which component has the strongest effect. To do this, a questionnaire was built based on previous studies and was answered voluntarily and anonymously by a group of virtual community members and a control group of students. Later, the resulting data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM).

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[1] Taringa is an Argentinian virtual community with more than 27 million members; in which users share videos, tutorials and recipes, and other users can give a score to the reviews.
[2] Taken from Internet Live Stats, retrieved from: http://www.internetlivestats.com/internet-users/

Literature Review

The aim of this study is to analyze what drives the intention to share in members of virtual communities. Previous literature about sharing intention was reviewed to find the most relevant constructs [3] influencing this intention. Studies in Economics, information management, and human behavior were present on the review. The final intention of this study was to investigate those motivators that influence people's cognition towards sharing, and hence their intentions, instead of those that are can be seen as resulting behaviors (e.g. entertainment, extrinsic rewards).

A study preformed by Zhang et al., (2014) divided the intention to share knowledge in two groups: intrinsic and extrinsic, based on where do the intention comes from. If the intention comes as an initiative of the person, it will be classified intrinsic. If the intention is a reaction to an external factor it will be considered extrinsic. The following constructs will be discussed considering this division.

As part of the intrinsic group the first construct chosen from the literature was enjoy in helping. Literature suggests that the leading intrinsic motivator for knowledge sharing is the joy of helping (Chiu et al., 2011; Shu & Wang, 2011, Paulini, Maher & Murty, 2014). Liao, To, & Hsu (2013) explained that people who share knowledge might be doing it moved by the desire to help others, and that enjoy in helping has an important role in knowledge contribution. Ye, Chen & Jin (2006) stated in their study that users enjoy sharing knowledge and feel rewarded simply by performing the task. Jin et al., (2013) also stated that enjoyment in helping is one of the most important values that users will get after sharing and that it is an important motivator of knowledge contribution. These three studies showed that enjoyment in helping has a significant effect towards sharing. Hence enjoy in helping was chosen for the study.

According to Jin et al., (2013), sometimes people's decisions about how to behave can often be predicted by the beliefs they hold on their capabilities rather than by what they are actually capable of accomplishing. These beliefs people hold about their

[3] Construct: A concept, model, or schematic idea built from other concepts or ideas.

capabilities can also be called self-efficacy. A person with high self-efficacy will hold high beliefs about their capabilities, and a person with low self-efficacy will hold low beliefs on their capabilities. In their study, Ye, Chen & Jin (2006) indicated that enhanced self-efficacy could motivate employees to contribute their knowledge with others. These two studies along with Hsu et al., (2007), show that self-efficacy is a significant predictor of knowledge sharing. Based on this evidence, self-efficacy is chosen to be part of this study as the second construct of the intrinsic group.

Lee & Jang (2010) described in their study how users who have shared information presented improved self-esteem afterwards, and say that people with high self-esteem tend to accept risks more willingly and are less affected by negative evaluation. In the process of knowledge sharing in a virtual community, first a user shares knowledge and then gets feedback. This feedback can be positive like a good qualification or an encouraging comment, or negative like a harmful comment, a bad qualification or the information shared might be ignored. Lee & Jang (2010) state that people with high self-esteem will not be stopped from sharing by the fear of negative feedback, and in their analysis confirmed (with a significance of $p < 0.01$) that people with higher self-esteem are more likely to share their knowledge than people with low self-esteem. Based on this result, self-esteem was chosen as a third construct inside the intrinsic group influencing sharing intention.

Reciprocity is the first construct of the extrinsic group. Fehr, E., & Gächter, S. (2000) state that positive reciprocity is deeply embedded in many social interactions. There is a correlation between individuals who believe in reciprocity and their intention to share knowledge (Chiu et al., 2006). Likewise Liao, To, & Hsu (2013) and Jin et al., (2013) found that reciprocity has a significant effect towards sharing. Chiu et al., (2006) in their paper affirmed that several studies, including fields such as Economics and Psychology, present reciprocity as an influential determinant of human behavior. According to this study, reciprocity is a behavioral response to both perceived kindness and unkindness. Liao, To, & Hsu (2013) believe that knowledge sharing can be perceived as an act of social exchange, which means that individuals who share knowledge with others tend to expect others to do the same as well. In their paper, Falk & Fischbacher

(2006) presented a formal reciprocity theory, which was applied adequately to different economic games. This theory assumes that reciprocity is based in both the intention to show reciprocity and the outcome of the action.

The second construct that forms part of the extrinsic group is reputation. According to Liao, To, & Hsu (2013) reputation can influence knowledge sharing in a person if it refers to the belief that he or she would benefit from showing others that he or she possesses some valuable expertise. Chiu et al., (2011) proposes that users contribute knowledge in "virtual communities of practice" expecting improved status and reputation. Jin et al., (2013) and Liao, To, & Hsu (2013) described that reputation is an important factor and has a significant influence towards knowledge sharing. This construct is based on the reaction of other users, using what they believe in order to enhance one's reputation. Based on this significant effect found in previous literature, reputation is added as the last construct for the analysis.

Some of the previously mentioned studies were performed to analyze knowledge sharing. The purpose of this study was to analyze the intention to share. According to Searle (1980) prior intention causes the action, so there is a relationship between the analysis of the intention and the actual share.

After choosing the constructs, the survey had to be assembled. The scales for reciprocity and enjoying helping were adapted from Kankanhalli et al. (2005). The scale items for reputation were adapted from Wasko & Faraj (2005) and the items for self-efficacy were adapted from Vijayasarathy (2004). Given that the survey was anonymous and voluntary the data of real share was not possible to gather. It was not feasible to link the answers of the survey to the users. Therefore intention to share was chosen as an alternative construct. Furthermore Liao, To, & Hsu (2013) describe that people who are proficient in sharing information are more willing to share knowledge with others. Hence this study employs proficiency to share as an indicator of the intention to share. The construct for intention to share was taken from Liao, To, & Hsu (2013).

Finally for self-esteem, the Rosenberg Self-Esteem Scale was used. This scale is a commonly used self-report instrument for evaluating individual self-esteem, explained in the study “Measuring Global Self-Esteem: Construct Validation of a Single-Item Measure and the Rosenberg Self-Esteem Scale” (2001), which has been cited by 1076 other studies and written by Richard W. Robins, Holly M. Hendin, and Kali H. Trzesniewski, researchers from the University of California. This evaluation consists of 10 items, each one of them scaled in a five-point Likert scale, and that provides results dividing people in ranks from high self-esteem to low self-esteem.

Related literature

Maher & Murty (2014) concluded that both enjoying helping and reputation, as intrinsic motivators, have a positive impact on attitude toward knowledge sharing. In their research they show that enjoying helping is the motive most commonly present, affecting 86% of the individuals of the study. Their results also showed that intrinsic motivations (Challenge, Fun, Recognition, Ideology) were more highly rated than extrinsic motivations (Career, Reward, Requirement). Liao, To, & Hsu (2013) did a study that suggests that four driving forces, which are utilitarian motivation, hedonic motivation, control belief (self-efficacy) and contextual force (sharing culture), also motivate users’ attitudes toward knowledge sharing. Although Liao, To, & Hsu (2013) and Maher & Murty (2014) consider attitudes instead of intention towards knowledge sharing, their results also indicate a significant relation between some of the constructs used in this study, i.e. self-efficacy, reputation and enjoy in helping, with the attitude towards knowledge sharing.

The study performed by Ye, Chen & Jin (2006) aimed to understand the factors influencing sharing intention. They used internal motivations such as enjoy in helping, self-efficacy and motivation, environmental factors like system usability, trust, and pro-sharing norms, and a knowledge factor called perceived value of knowledge. In their study Ye, Chen & Jin (2006) found that self-efficacy, enjoy in helping, self-image, trust and system usability influence in knowledge contribution intention. This study analyzed three categories of factors and nine constructs. It will be better to use fewer factors in the analysis and have more detailed findings.

Finally the study performed by Jin et al., (2013) combined self-efficacy, enjoying helping, reputation and reciprocity to explain indirectly users intention to continue sharing knowledge. Their model suggests that reputation, enjoying helping, and reciprocity, are positively related with self-efficacy and with the confirmation of the users' expectations after sharing. Later they analyzed the relation between confirmation and self-efficacy with the intention to continue sharing knowledge. The relationship between, enjoying helping, reputation and reciprocity with the intention to share is not clear. Apparently it depends on their relation with other factors (self-efficacy, confirmation and satisfaction) to explain their influence towards sharing intention.

Hypotheses

The following hypotheses were formulated based on the previously reviewed literature. Each hypothesis is aimed to test one construct, and the method used in this study will allow us to, aside from testing the hypotheses, identify which one has the strongest effect towards the intention to share.

H1: Enjoying helping has a positive impact on the intention toward knowledge sharing.

H2: Self-efficacy has a positive impact on the intention toward knowledge sharing.

H3: Self-esteem has a positive impact on the intention toward knowledge sharing.

H4: Reciprocity has a positive impact on the intention toward knowledge sharing.

H5: Reputation has a positive impact on the intention toward knowledge sharing.

Methodology and Implementation

In previous studies where the objective was to find incentives behind knowledge sharing, the most common method used to gather data is a well-defined survey sent to members of online communities. Given this, to test the hypotheses of this study a survey was created and sent to the virtual community members and, as a control group, to students. This survey measured six constructs that where adapted from previous literature: enjoy in helping, reciprocity, reputation, self-efficacy, self-esteem and intention to share (proficiency to share). Once the survey was completed and reviewed, it was sent to be answered voluntary and anonymously.

The virtual community group was conformed by users of an online community. TripAdvisor was used as platform for sending the questionnaire to high-rank members (users that due to their high activity in the community have a special status like *destination experts*) and to intermediate members (users that are part of the community who lack of any special status). The criteria for selecting high-ranked members and intermediate members were the ranking and the number of comments of said users inside the community. High-ranked members must have the highest rank inside the community, which is "destination expert", along with more than 500 reviews. Intermediate community members must have between 200 and 499 comments.

For the control group, using social networks, the survey was sent to a group of students with similar characteristics in gender and age as the virtual community members. The students who answered the survey formed the control group. The goal was to analyze if the results between samples of high-ranked members differ from the control group, and analyze if we can see a trail of evidence of this change in the intermediate group. The questionnaire was sent to 80 high-ranked and 100 intermediate but only 11 high-ranked and 10 intermediate community members answered back. Because of this low rate of response it was not feasible to treat high-ranked and the intermediate members as two different samples. Instead of this, one group (Communities) was built using both types of community members, and compared with one control group.

To analyze the data obtained, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used, as in Chiu & Fang (2009) and Liao, To, & Hsu (2013). PLS-SEM is a structural technique that can specify both the relationships among the constructs built using the questions of the survey, and the relationship between each question and its construct (Wold, 1989). This technique works with two models: measurement model and structural model. The measurement model shows the amount of variance of the construct explained by the question. The structural model displays the relationship between the constructs. For this study, the PLS-SEM was applied using the software SmartPLS[4].

Results

Tables 1 and 2 show the descriptive statistics of both community members and control group.

Table 1. Descriptive statistics of the responders		**Community group**	**Control group**
Gender	male	12	9
	female	9	10
Age	<15	0	0
	15-20	1	2
	21-25	14	15
	26-30	4	2
	31-35	1	0
	36-40	0	0
	41-45	0	0
	46-50	0	0
	>50	1	0
Level of studies	High school	0	1
	Bachelor's studies	7	10
	Master's studies	13	8
	Doctoral studies	1	0
Field of study	Social sciences	13	13
	Business & Business related	4	3
	Engineering	2	3
	Medicine	1	0
	Pure Sciences	0	0
	IT & Systems engineering	1	0

[4] SmartPLS is a professional statistical software package that enables users to do Structural Equation Modeling or PLS path modeling. Retrieved from http://www.smartpls.com

In Table 1 we can see that we have almost the same amount of females in both groups, and a difference of three males between communities and control. The higher concentration of subjects in both groups is located between the ages 21 and 25 years, with few subjects in the immediate higher and lower categories. Despite the outlier in the virtual community group, and given the distribution of the subjects in the different ages slots, both groups are sufficiently similar regarding age and gender and capable to be compared.

The level of studies is less similar between groups. The control group was intended to be as similar as possible to the community group so the survey was sent to a group of students as comparable as possible to the community group. Unfortunately one member of the community group with doctoral studies answer the survey and no one with this level of studies answered in the control. The same happened with a person with high school studies in the control group. These two details make the community group and the control group less similar, but noticing that the majority of subjects are in the groups of bachelor's studies and master's studies (20 in community and 18 in control) we can conclude that the community group and control are comparable. The field of studies of both groups is also similar. There are the same number of subjects in the group of Social Sciences, and a difference of one subject in the groups of Engineering, Medicine, and IT & Systems engineering. Given that the majority of subjects are in the Social Sciences group, 65% of subjects for the community and 68% for the control, these two groups are comparable for analysis.

Table 2 shows descriptive statistics of the answers for all the questions of the different type of subjects, high-ranked virtual community members, intermediate community members, and control. Here we can see that almost all the groups reached the maximum answer (7) but almost no group reached the minimum answer (1). In six of the questions the mean of the answers of the high-ranked group is higher than the intermediate, and the intermediate higher than the control; and in ten questions the mean of the high-ranked is higher than both intermediate and control. With these results we can say that high-ranked members have a higher intention to share than the intermediate members and the control. It is also possible to say that the constructs and the questions were correctly chosen since the average of the questions are higher for all the cases in the high-ranked community members and in most of the cases for intermediate community members. This could be expected given high-ranked members share more than intermediate and control.

Also in table 2 we can see the different questions that formed part of each constructs. For example the construct "Enjoy", used for testing H1, was built using the questions Enj1, Enj2, Enj3, and Enj4 from the survey. (See survey Appendix 1)

Table 2. Descriptive statistics of the answers

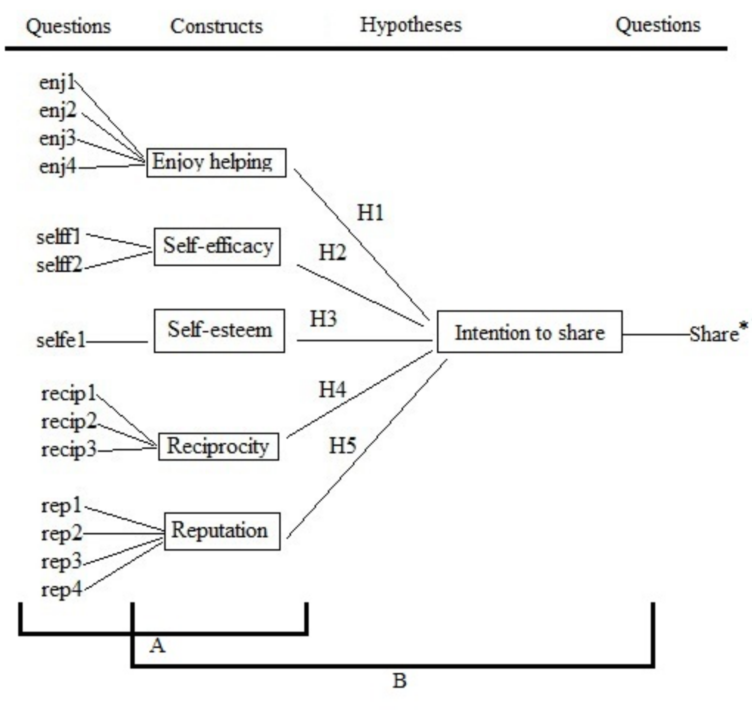
Question	Group	Observations	Minimum	Maximum	Mean	Std. Deviation
Enj1	VC(H)	11	5	7	6.636	0.674
	VC(I)	10	4	7	6.200	1.033
	Co	19	5	7	6.526	0.612
Enj2	VC(H)	11	5	7	6.455	0.688
	VC(I)	10	5	7	6.200	0.632
	Co	19	5	7	6.526	0.612
Enj3	VC(H)	11	5	7	6.364	0.674
	VC(I)	10	5	7	6.400	0.699
	Co	19	5	7	6.526	0.612
Enj4	VC(H)	11	5	7	6.273	0.786
	VC(I)	10	4	7	6.000	1.054
	Co	19	4	7	6.263	0.933
Recip1	VC(H)	11	2	7	5.455	1.293
	VC(I)	10	2	7	4.400	1.647
	Co	19	3	7	5.000	1.155
Recip2	VC(H)	11	2	7	5.000	1.414
	VC(I)	10	1	7	3.800	2.044
	Co	19	2	7	4.895	1.595
Recip3	VC(H)	11	2	7	4.818	1.601
	VC(I)	10	1	7	4.300	2.003
	Co	19	2	7	5.000	1.826
Rep1	VC(H)	11	2	7	5.364	1.502
	VC(I)	10	3	7	5.000	1.155
	Co	19	2	7	5.632	1.257
Rep2	VC(H)	11	4	6	5.182	0.982
	VC(I)	10	1	7	4.500	1.780
	Co	19	2	7	4.684	1.765
Rep3	VC(H)	11	3	6	4.545	1.214
	VC(I)	10	1	7	3.400	1.955
	Co	19	1	7	3.632	2.216
Rep4	VC(H)	11	3	6	5.091	1.221
	VC(I)	10	1	7	4.700	1.703
	Co	19	1	7	4.000	1.972
Selff1	VC(H)	11	2	7	5.364	1.433

	VC(I)	10	1	7	4.900	1.595
	Co	19	2	7	4.737	1.098
Selff2	VC(H)	11	5	7	5.909	0.701
	VC(I)	10	2	7	5.500	1.581
	Co	19	2	7	5.368	1.342
Selfe1	VC(H)	11	25.6	39.2	32.436	4.615
	VC(I)	10	20.8	39.2	31.600	5.710
	Co	19	18.7	36.8	28.126	7.036
Share	VC(H)	11	5	7	5.636	0.674
	VC(I)	10	4	7	5.000	1.054
	Co	19	1	7	4.684	1.701

VC(H):Virtual community group, high-ranked.
VC(I):Virtual community group, Intermediate.
Co: Control group.

In figure 1 we can see the research model used to analyze the resulting data, which was built using the questions and the constructs. Here we can also see the two different models, measurement and structural, considered in the PLS-SEM.

Figure 1. Research model



A: Measurement model
B: Structural model
*The relationship between Share and the Intention to share is also part of the measurement model

The model must be first tested for validity so it could be used to analyze the data. According to Fornell and Larcker (1981), the benchmarks recommended for a model to be suitable to use, is that the constructs have a Composite Reliability (CR) higher than 0.7 and an Average Variance Extracted (AVE) higher than 0.5. The model exhibits satisfactory reliability and convergent validity (Appendix 2) given that all the constructs are above the benchmark. The second step for testing the validity of the model is to check for discriminant validity. For achieving this, the square root of each construct's AVE must be larger than correlation of said construct with other constructs (Fornell and Larcker, 1981). The model accomplished discriminant validity. (Appendix 3)

Before comparing the results from the community group and the control, it is important to test if there are significant differences between both groups. To test for differences a multi-group analysis[5] was performed, using a tool from SmartPLS called PLS Multi-Group Analysis (PLS-MGA). The PLS-MGA is a significance test that evaluates if pre-defined data groups have significant differences in their group-specific parameter estimates[6]. This method evaluates if differences between the coefficients of each model (built using the answers of the survey) are significant.

For this method to confirm a significant difference between the two groups, the p-value must be smaller than 0.05 or higher than 0.95. Even though according to table 3 there is no p-value smaller than 0.05 or higher than 0.95, we can see some strong differences between the two groups, for example between the coefficients of enjoy. In the table we can see that the difference between enjoy's coefficients is 0.303 and the difference between its p-value is 0.199, just 0.149 points away of being significant. The p-value from the difference between the self-esteem's constructs is the second closer to be significant; it is 0.104 away from reaching the higher bound 0.95. In these two cases (enjoy, self-esteem), their coefficients from the path analysis are larger in the community group than in the control group. These results can be expected as we assume that the community members present higher intention to share than the control group.

[5]The multi-group analysis allows testing if pre-defined data groups have significant differences in their group-specific parameter estimates. Retrieved from: http://www.smartpls.de/documentation/pls-multigroup-analysis

[6] Retrieved from: http://www.smartpls.de/documentation/pls-multigroup-analysis

Table 3. PLS-MGA Between Community group and Control group

	Enjoy	Self-efficacy	Self-esteem	Reciprocity	Reputation
Community group **Share**	0.644	0.542	0.504	0.338	0.609
Control group **Share**	0.341	0.721	0.374	0.490	0.644
Difference	0.303	0.179	0.130	0.152	0.035
p-Value Community vs. Control	0.199	0.360	0.846	0.705	0.634

PLS analysis was used to find if the constructs had a significant effect towards the intention to share. This method relies on a nonparametric bootstrap procedure (Efron and Tibshirani, 1986; Davison and Hinkley, 1997) to test the significance of the estimated path coefficients. Table 4 shows the standardized PLS path coefficients of the structural model and the level of significance after testing the t-statistics of the coefficients. Here we can see that the most important factor influencing the intention to share in the community group is enjoying helping, followed by reputation, self-efficacy and self-esteem. These results are in line with the literature, which suggests that enjoy in helping is the main motivator behind sharing.

Self-esteem and reputation show a higher degree of significance in their relationship towards sharing intention in the community group than in the control group. In the review of the literature was stated that people with high self-esteem will not be stopped from sharing information by the fear of negative feedback. Based on the results of the path analysis we can then conclude that people with high self-esteem would not be stopped from sharing information likewise inside virtual communities. The higher significance in reputation can be understood since people, who are member of a community, care about what they share inside the community, care about what other members think about their contributions, therefore care about their reputation.

Self-efficacy show a higher level of significance in the control group than in the community group. This result might not be seen as if community members have a lower self-efficacy than non-community members. Rather it might be seen as inside community members self-efficacy is not one of the main motives behind sharing intention (knowing that its significance level is forth after enjoying in helping, reputation and self-esteem.)

Table 4. PLS-SEM Path Coefficients between constructs and Intention to share

	H1 Enjoy	H2 Self-efficacy	H3 Self-esteem	H4 Reciprocity	H5 Reputation
Community group					
Intention to hare	0.644***	0.542**	0.504**	0.338	0.609***
Control group					
Intention to hare	0.341	0.721***	0.374	0.49	0.644**

* P < 0.05

** P < 0.01

*** P < 0.001

Control group

The analysis of the control group model followed the same mechanics as for the community group. All the constructs in the model are valid since they displayed convergence validity and discriminant validity.[7].

The PLS-SEM for the control group showed that the most important influence towards the intention to share were self-efficacy followed by reputation, given that they have the higher coefficients. The bootstrap analysis revealed that self-efficacy and reputation have a significant effect at a 1.0% and 0.1% level respectively.

Limitations

The survey used in this study was anonymous and voluntary, so data on actual sharing was not possible to gather. Instead of actual sharing, intention to share was measured based on the proficiency to share of users.

Since the groups were conformed by participants based on their willingness to be part of the study (answered the survey), there could be self-selecting bias on the data. The questionnaire was sent to 81 participants, from which only 21 answered back. This means that the results of this study used the 25.9% of the population that received the survey. This bias can influence the results by enhancing constructs, for example enjoy helping. People whose intention to share is mainly driven by enjoy helping would be more

[7] There is no CR less than 0.7 and no AVE is less than 0.5 (Appendix 4). The square root of each construct's AVE is larger than its correlation with other constructs (Appendix 5)

motivated to answer the survey, than a person whose intention to share is mainly influenced by enhancing their reputation within the community, because they will not get any benefit in return of being part of this study.

As part of the study, a second virtual community called Taringa was intended to be used for being compared with Tripadvisor and the control, but from 100 surveys sent only 4 users responded. Therefore this second virtual community was not feasible to use and a problem of external validity could occur. Consequently the order of influence of the constructs might also change if other kind of community is analyzed.

The results of this study might be suitable to be compared with other studies performed on similar virtual communities, for example communities based, formed, or oriented in leisure activities.

Discussion and conclusion

It is important to state the fact that this study was based on 21 community members whereas some studies in the literature are based on around 100 users. Even though the sample was relatively small, the methodology and tools used allow the study to derive significant results. After evaluating the results obtained in the analysis we can see that enjoying helping has the biggest influence in sharing intention. This finding might be examined considering that the virtual community used for the study is formed by people sharing information based on their leisure time. If the study was oriented on an organizational virtual community located inside a company, enjoying helping might not be the principal influence towards sharing. Reputation, elf-efficacy and self-esteem also exhibited significant effects on sharing intention.

It makes sense that reputation and self-efficacy had significant effects on the intention to share in the community group, since the community rank its members based on their contributions. This detail can serve as an incentive to the users to differentiate themselves from the rest by gaining a higher status, which can only be obtained by sharing information, therefore increasing their reputation. In the case of self-efficacy users need to think that their knowledge is valuable beforehand, for then sharing it with the community. In this study reciprocity didn't show a significant effect towards knowledge sharing. A reason for this might be the fact that high-ranked or even intermediate users are more driven by enjoying and getting recognition, rather than seeking for new information, for which reciprocity may be useful.

The control group showed significant effects on self-efficacy ($p<0.001$) and reputation ($p<0.01$) towards knowledge sharing intention. The analysis of these results in comparison with the results from the community group, suggests that reputation and self-efficacy might be drivers for sharing intention in a more general way, since their relationship was significant in both groups. Thus enjoy in helping and self-esteem are left as proper drivers of the intention to share for community members.

As mention before, the sample was relatively small and the information was anonymous and voluntary. Therefore for further research it will be useful to have a bigger sample, and to get actual data on sharing. This way more solid conclusions could be dropped from the analysis.

This study had to merge high-ranked community members and intermediate community members due to the lack of responses. For further studies it could be better to have a sample of high-ranked members, a sample of intermediate and a sample for control. This way the results might differ showing a clearer difference between high-ranked, intermediate and control.

A way of getting a bigger sample could be that the owners of a virtual community can run the survey making it mandatory to their users in order to continue as part of the community. If this is done self-selecting bias will also be diminished, but the survey must be as simple and as short as possible so the risk of people dropping out the community instead of filling the survey can be reduced to the minimum possible.

Finally as a last step up, self-esteem can be tested with a different test, may by more thorough than the Rosenberg Scale, which could inquire more time and analysis, so the self-esteem data of the study will rely on the output of a more exhaustive test.

Appendix

Appendix 1.

Survey

Gender

- Male
- Female

Age

<15

15-20

21-25

26-30

31-35

36-40

41-45

46-50

>50

Level of studies

- High school
- Bachelor's studies
- Master's studies
- Doctoral studies

Field of studies

- Social Sciences (Economics, Psychology, Law, Sociology, Political science, History, Education, Communication studies, Anthropology)
- Business & Business related (Business, Marketing, Finance, HR,

Accounting)

- Engineering (Chemical Engineering, Civil engineering, Electrical engineering, Mechanical engineering)
- Medicine
- Pure Sciences (Mathematics, Chemistry, Physics)
- IT or Systems engineering

All items in the questionnaire (except self-esteem) adopted a seven-point Likert scale, with 1 representing "Strongly Disagree" and 7 representing "Strongly Agree".

Enjoying helping

Questions:

- Enj1: I enjoy sharing my knowledge with others.
- Enj2: I enjoy helping others by sharing my knowledge.
- Enj3: It feels good to help someone else by sharing my knowledge.
- Enj4: Sharing my knowledge with others gives me pleasure.

Reciprocity

Questions:

- Recip1: When I share my knowledge, I believe that my queries will be answered in future.
- Recip2: When I share my knowledge, I expect somebody to respond when I'm in need.
- Recip3: When I contribute with knowledge, I expect to get back knowledge when I need it.

Reputation

Questions:

- Rep1: I earn respect from others by sharing knowledge.
- Rep2: I feel that sharing knowledge improves my status.

- Rep3: I share knowledge to improve my reputation.
- Rep4: I feel that sharing knowledge improves my image.

Self-efficacy

Questions:

- Selff1: I have the expertise needed to provide valuable knowledge.
- Selff2: I feel confident that I can share valuable knowledge.

Share

Questions:

- Share: I am proficient in sharing knowledge.

Self-esteem (The Rosenberg Self-Esteem Scale)

The score of the test is accounted as Selfe1.

All items are answered using a 5-point Likert scale format ranging from strongly agree to strongly disagree.

1.On the whole, I am satisfied with myself.

2. At times I think I am no good at all.

3. I feel that I have a number of good qualities.

4. I am able to do things as well as most other people.

5. I feel I do not have much to be proud of.

6. I certainly feel useless at times.

7. I feel that I'm a person of worth, at least on an equal plane with others.

8. I wish I could have more respect for myself.

9. All in all, I am inclined to feel that I am a failure.

10. I take a positive attitude toward myself.

Scoring

Items 2, 5, 6, 8, 9 are reverse scored. Give “Strongly Disagree” 1 point, “Disagree” 2 points, “Neutral” 3 points, and “Agree” 4 points, “Strongly Agree” 5 points. Sum scores for all ten items. Keep scores on a continuous scale. Higher scores indicate higher self-esteem.

Appendix 2

	Items	**CR**	**AVE**
Enjoy	4	0.944	0.809
Reciprocity	3	0.948	0.860
Reputation	4	0.890	0.671
Self Efficacy	2	0.900	0.819
Self Esteem	1	1.000	1.000
Share	1	1.000	1.000

Appendix 3

Discriminant Validity						
	Enjoy	**Reciprocity**	**Reputation**	**Self Efficacy**	**Self Esteem**	**Share**
Enjoy	0.899[a]					
Reciprocity	0.358	0.927[a]				
Reputation	0.336	0.436	0.819[a]			
Self Efficacy	0.307	0.486	0.692	0.905[a]		
Self Esteem	0.126	0.066	0.209	0.334	1.000[a]	
Share	0.644	0.338	0.609	0.542	0.356	1.000[a]

Note: [a]The numbers in the diagonal row are square roots of the AVE

Appendix 4

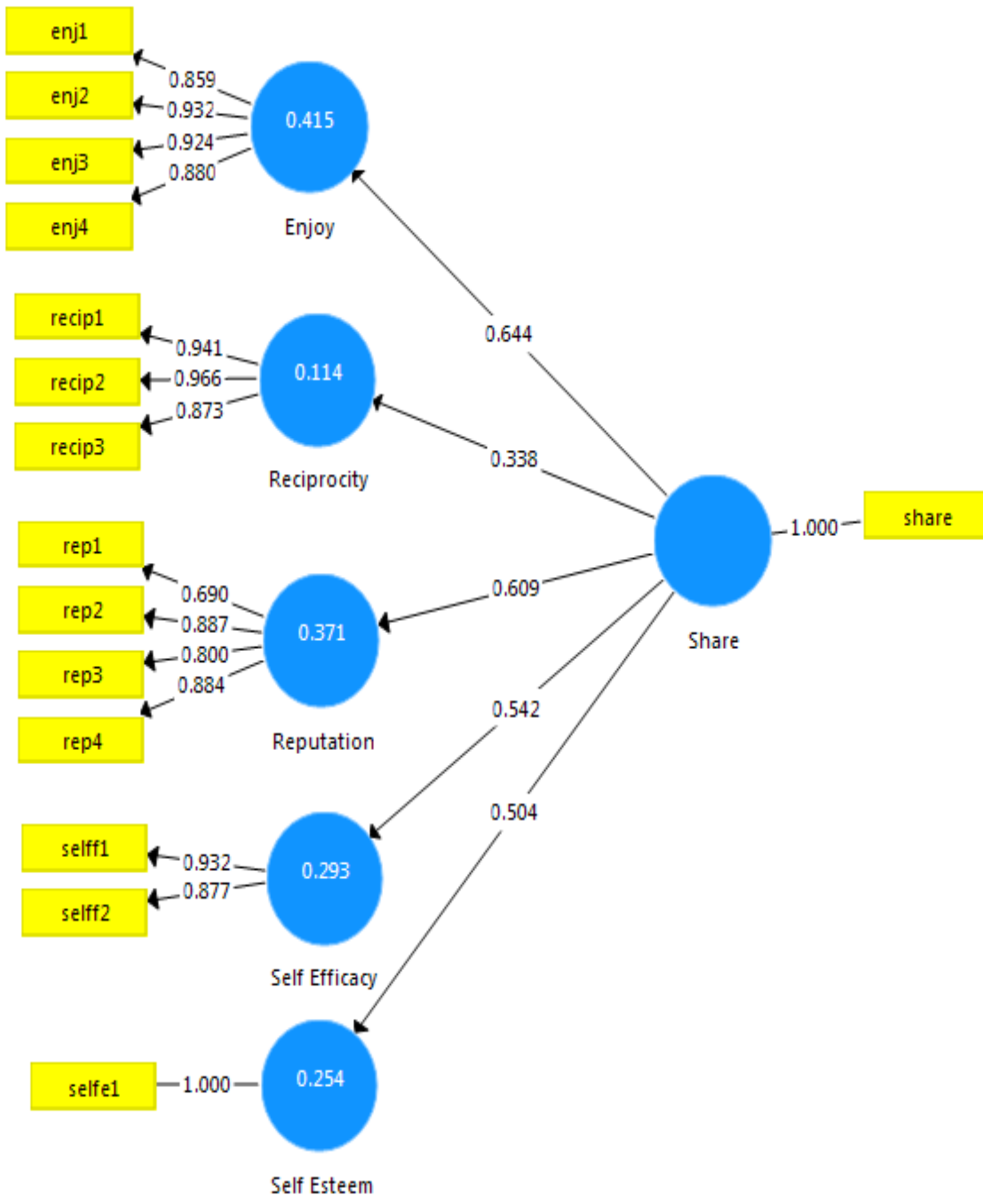
	Items	CR	AVE
Enjoy	4	0.812	0.525
Reciprocity	3	0.919	0.791
Reputation	4	0.885	0.660
Self Efficacy	2	0.932	0.873
Self Esteem	1	1.000	1.000
Share	1	1.000	1.000

Appendix 5

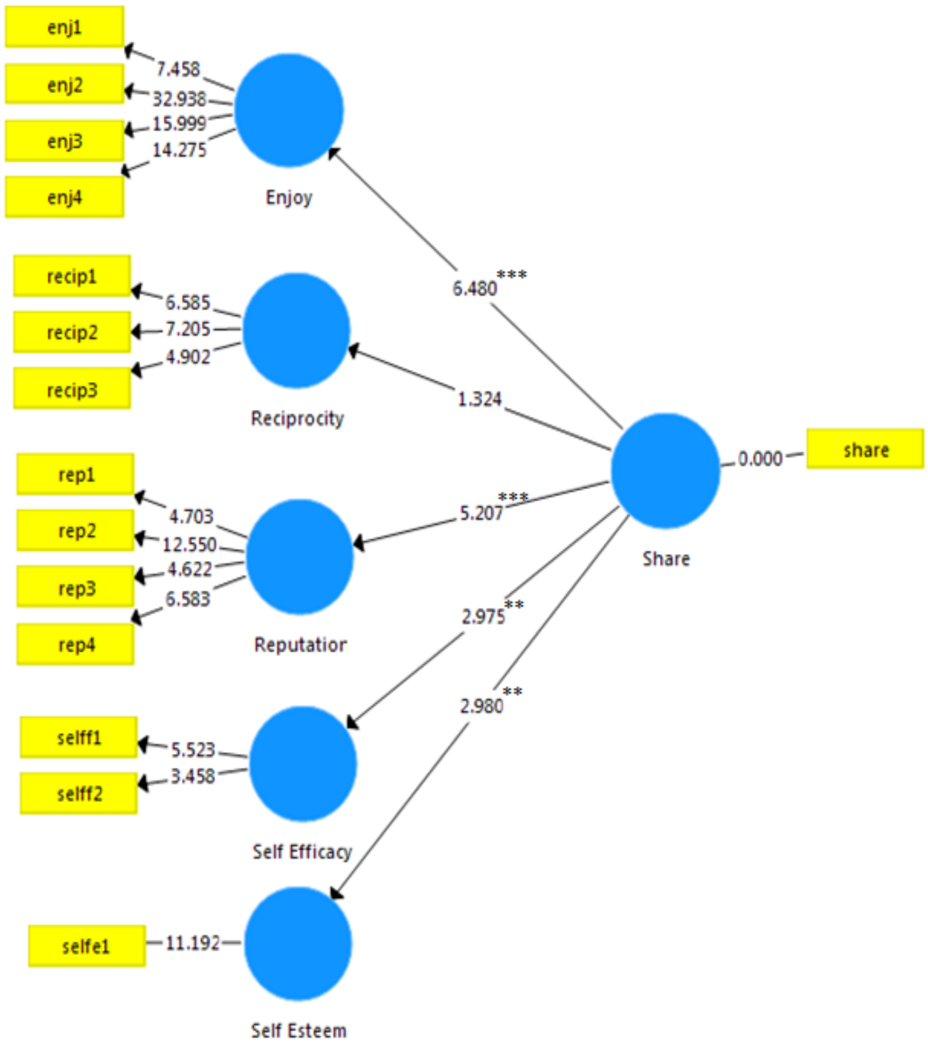
Discriminant Validity	Enjoy	Reciprocity	Reputation	Self Efficacy	Self Esteem	Share
Enjoy	0.725[a]					
Reciprocity	0.123	0.890[a]				
Reputation	0.096	0.668	0.812[a]			
Self Efficacy	0.217	0.347	0.515	0.935[a]		
Self Esteem	-0.096	0.305	0.325	0.561	1.000[a]	
Share	0.341	0.490	0.644	0.721	0.374	1.000[a]

Note: [a]The numbers in the diagonal row are square roots of the AVE

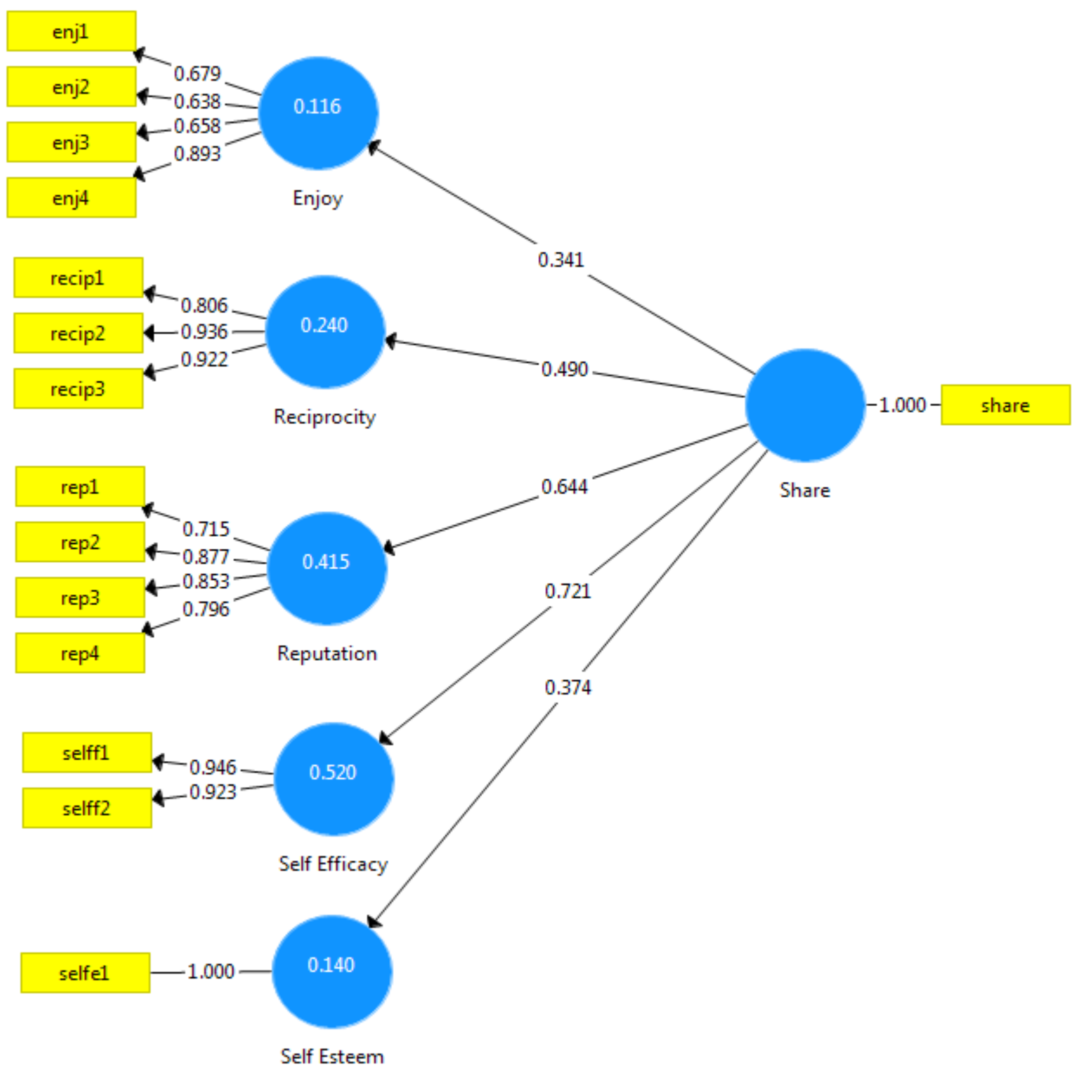
PLS-SEM Virtual community



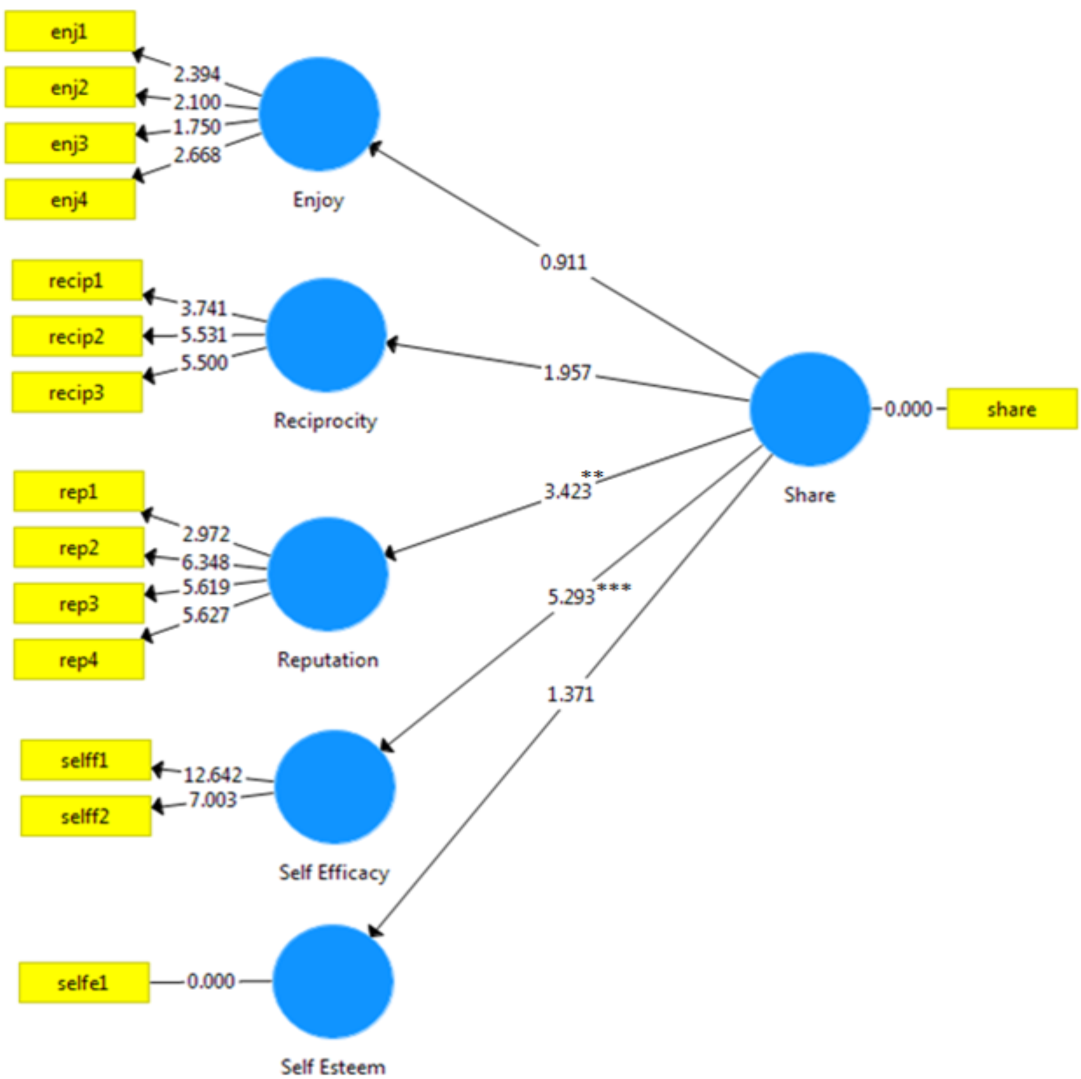
PLS-SEM Virtual community (Bootstrap)



PLS-SEM Control group



PLS-SEM Control group (bootstrap)



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