VINE Journal of Information and Knowledge Manag
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Journal:	*VINE Journal of Information and Knowledge Management Systems*
Manuscript ID	VJIKMS-05-2023-0125.R4
Manuscript Type:	Research Paper
Keywords:	virtual communities, knowledge sharing, knowledge-sharing self-efficacy, perceived relative advantage, social identification, norm of reciprocity

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Abstract

Purpose - Knowledge sharing is essential for the management and long-term sustainability of virtual communities. Although previous research has examined the factors that influence knowledge sharing in VCs, it has not determined whether their influence is equal across the different types of VCs. Thus, the aim of this study is to examine the influence of personal and contextual factors on knowledge sharing in two different types of VCs (VCs of interest and virtual learning communities).

Design/methodology/approach - A survey methodology was employed to collect data. We obtained 261 valid responses through an online survey distributed to various virtual communities of interest and virtual learning communities. Most respondents (73.95%) were aged between 21 and 30 years, were female (66.67%), and were enrolled in university programs (56.32%). Structural equation modeling was utilized to test the study's hypotheses.

Findings - Our results show that the type of VC moderates the positive influence of knowledge-sharing self-efficacy and perceived relative advantage on knowledge sharing. More specifically, the influence of self-efficacy on knowledge sharing is stronger in VCs of interest, whereas the influence of perceived relative advantage is stronger in virtual learning communities. Moreover, the influence of social identification on knowledge sharing is similar in both types of VCs. We also found that the norm of reciprocity has a nonsignificant influence on both types of VC.

Originality – We contribute to previous research on the effects of personal and contextual factors on knowledge-sharing models by highlighting the influential role of the type of VC.

Keywords: virtual communities; knowledge sharing; knowledge-sharing self-efficacy; perceived relative advantage; social identification; norm of reciprocity

1. Introduction

The popularity of virtual communities (VCs) has evolved significantly, driven by advances in information and communication technologies (Martínez-López *et al.,* 2016; Zhao *et al.*, 2022). This trend was accelerated by the COVID-19 pandemic, which intensified the use of digital tools already present in organizations and society (Abidi *et al.,* 2023; Fauzi *et al*., 2023; Soto-Acosta, 2020), further highlighting the need for effective online collaboration and interaction in virtual environments. Additionally, generative artificial intelligence (AI) has undergone a significant evolution, transforming interactions in various fields, including education (González-Anta, 2024). VCs and learning groups can leverage AI to improve knowledge sharing and participation by optimizing information management, facilitating interactions, and generating content (Hwang and Chien, 2023).

VCs have attracted cross-disciplinary attention from scholars and practitioners because they can fundamentally change the way we work, socialize, date, or learn (Fauzi, 2019; Thompson, 2011; Zhao *et al.,* 2022). VCs, aka online communities, are groups of individuals who interact through online platforms, typically centred around shared interests, goals, or activities (Alyouzbaky *et al*., 2024; Wang N. *et al.,* 2021). These communities can exist across various digital spaces, such as social media, forums, or collaborative tools, and they are characterized by the exchange of information, support, and engagement without the need for physical proximity (Chen *et al*., 2019). With the evolution of technology, VCs have expanded to include more immersive environments, such as virtual worlds and metaverse spaces (van Brakel *et al*., 2023).

VCs share the common feature that their members can interact with one another (e.g., asking questions and providing answers on a specific topic) through internet forums, chat rooms, or social networks (e.g., X (formerly Twitter), WeChat, Facebook, Telegram, or LinkedIn). However, there is great diversity among VCs, which may differ significantly in their objectives, characteristics, and dynamics (Abouzahra and Tan, 2014; Martínez-López *et al.,* 2016). For instance, members of interest-based VCs voluntarily share knowledge online with strangers who have similar interests, covering a wide range of topics such as business, politics, education, and health (Kang *et al.*, 2016; Luo *et al.,* 2021). These communities contrast with virtual learning communities in higher education, where classmates interact and engage in dialogue through both asynchronous and synchronous communication. In this type of VC, instructors establish learning objectives, guide students through the learning process, and foster the creation of collective knowledge (Liu *et al*., 2010; Ouyang *et al*., 2020).

The viability of VCs relies on the active participation of their members, particularly through knowledge sharing (e.g., Chen *et al*., 2019; González-Anta *et al.,* 2023; Jin *et al*., 2015; Zhang et al., 2019). Knowledge sharing in VCs is a communication process that involves both the provision and acquisition of knowledge by community members. However, this process is inherently complex because, whereas explicit knowledge is easily accessible, personal and subjective insights (e.g., tacit knowledge) are much harder to convey in VCs (Abidi *et al*., 2023; Dzenopoljac *et al*., 2024; Wang N *et al*., 2021).

Previous research has investigated various specific factors that influence knowledge sharing in VCs (e.g., Chang and Chuang, 2011; Chen and Hung, 2010; Ergün and Avcı, 2018; Fauzi, 2019; Fauzi *et al*., 2023; Lin et al., 2009; Wang, J. *et al*., 2019; Ye *et al*., 2015). Despite growing interest in VCs, limited attention has been paid to the way various VC characteristics impact these factors. Consequently, there is a significant gap in understanding the potential moderating role of VC types. Therefore, this study explores whether different types of VCs moderate the influence of personal and contextual factors on knowledge sharing. Our findings may contribute to the development of more effective, tailored strategies for fostering knowledge sharing in different types of VCs, ultimately enhancing their sustainability and value for participants.

2. Literature review

2.1. The influence of personal and contextual factors on knowledge sharing in VCs

To gain greater insight into why individuals share knowledge in VCs, previous research has developed models that incorporate both personal and contextual-relational factors that drive the knowledge-sharing process (Hernández-Soto *et al.,* 2021). Although these models do not consistently include the same variables in all the studies, our literature review highlights that key factors influencing knowledge sharing in VCs include personal factors such as knowledge-sharing self-efficacy and perceived relative advantage and contextual-relational factors such as social identification and the norm of reciprocity (e.g., Alyouzbaky *et al.*, 2024; Chang and Chuang, 2011; Chen and Hung, 2010; Fauzi, 2019; Fauzi *et al*., 2023; Karaoglan Yilmaz, 2017; Wang, J. *et al.*, 2019; Wang, N. *et al.,* 2021).

Knowledge-sharing self-efficacy refers to individuals' reliance on their abilities related to writing, answering questions, and engaging in discussions with others, which facilitates knowledge sharing (Wang, N *et al.,* 2021; Lin *et al.*, 2009; Thompson, 2011). Some studies have found that knowledge-sharing self-efficacy plays an influential role in guiding virtual community members' knowledge-sharing behavior (Hsu *et al.* 2007; Wang, N. *et al.,* 2021). Lin *et al.* (2009) also found that community members who had higher knowledge-sharing self-efficacy were more likely to contribute their knowledge to others in professional VCs.

Second, perceived relative advantage refers to the awareness of likely advantages and benefits that knowledge-sharing behavior in a VC will produce and extend to the individual. Previous research has found that perceived relative advantage positively influences knowledge sharing in professional VCs (Chen and Hung 2010; Lin *et al.*, 2009), suggesting that individuals share knowledge when their cognition indicates that they will obtain a benefit in return. These benefits obtained in return may involve achieving better relationships or a relevant position in a virtual community of practice (Lin *et al.*, 2009), gaining enriching knowledge from others, getting support, being viewed as more skilled, knowledgeable, and respected, or receiving help faster from others when needed (Chen and Hung 2010).

Third, social identification refers to community members' sense of belonging and positive feeling towards their VC (Chiu *et al.*, 2006; Huang *et al.,* 2020). Identification is considered an important resource for overcoming the challenges posed by the virtual environment (Chiu *et al.*, 2006; Kim *et al.,* 2019). In this regard, empirical research has found positive and significant relationships between social identification and knowledge shared by individuals (Chang and Chuang, 2011). When people feel part of a VC, they find it easier to share, which makes them more willing to contribute to the community (González-Anta *et al.,* 2023). Thus, when social identification is strong, community members' perception of the community's social unity or togetherness is higher, which facilitates cooperation and knowledge sharing.

Finally, the norm of reciprocity refers to the "embedded obligations created by exchanges of benefits or favors among individuals" (Chen *et al.*, 2009, p. 24). Knowledge sharing is a voluntary action carried out by individuals that may be influenced by their perception of what they can receive from others. According to the Social Exchange Theory (Blau, 1964), individuals develop norms about reciprocity and expect that there will be a benefit from collective actions such as contributing knowledge to the community. Specifically, knowledge sharing in VCs involves a social exchange interaction among users, based on expected and positive returns. Several studies have demonstrated the positive effect of reciprocity on knowledge sharing in VCs (e.g., Chang and Chuang, 2011). However, contrary to expectations, other research has found either a non-significant or negative relationship (Cheng and Hung, 2010), whereas some have emphasized the mediating or moderating role of specific variables in shaping knowledge sharing (Luo *et al.*, 2021; Pai and Tsai, 2016). These mixed findings point to the need for further research in this area.

Although previous research allows us to better understand knowledge sharing in VCs, it failed to ascertain whether these relationships are equal across the different types of VCs studied. As we have seen, most prior studies have examined these variables in different types of VCs without considering their distinctive features. However, a meta-analysis by Abouzahra and Tan (2014) provides initial findings showing that the type of VC may play a moderating role in some determinants of knowledge sharing, highlighting the need to consider the type of VC in knowledge sharing models. Thus, we aim to contribute to this field of research by comparing two types of VCs: VCs of interest and virtual learning communities.

2.2. The moderating role of the type of virtual community

To study the differences between VCs, it is important to establish specific dimensions of VCs that can be compared. In the literature, there is no consensus about the types of VCs and no universally accepted typology (Martínez-López et al., 2016; Zhao et al., 2022). Nevertheless, we base our analysis on two key dimensions that can be used to compare VCs of interest and virtual learning communities: the strength of the social bond and the intentionality of the gathering (Henri and Pudelko, 2003). On the one hand, the strength of the social bond refers to the process of setting up the VC, which can vary from a simple gathering to a group of people with a high degree of cohesion and involvement. On the other hand, the intentionality of the gathering refers to the appearance of common objectives and interdependence among the participants. Both dimensions sequentially increase from less complexity to greater complexity. Thus, some VCs are characterized by stronger social bonds among their members –e.g., feelings of cohesion and emotional attachment- and stronger intentionality of gathering and interdependence, whereas others are weaker in these dimensions. Considering these two dimensions, VCs of interest show a low level in both dimensions, whereas virtual learning communities show a medium to high level.

On the one hand, VCs of interest are made up of individuals who share a common interest and gather to exchange information about a given topic (Henri and Pudelko, 2003; Zareie *et al*., 2019). However, unlike in formal groups with a shared mission, in this type of VC, members are not motivated by a common goal. Thus, there is no expectation that everyone will engage in knowledge sharing, and so the responsibility for sharing is diluted (Thompson, 2011). Moreover, the members of a VC of interest identify more with the topic of interest than with its members. Therefore, there is a low level of interdependence and intentionality, which, along with the potential anonymity in this type of VC, makes the ties among participants weak.

On the other hand, virtual learning communities are mainly composed of students who may belong to the same class or institution and may or may not be geographically dispersed (Henri and Pudelko, 2003). Members gather in the community to learn by participating in a collaborative project (Donelan and Kear, 2024). Thus, they have a declared shared goal, which is learning (Tan and Lee, 2018). Members do not play a role in the creation of the community, and its course is dependent on the educational program they serve. Members contribute knowledge to reach the objective, establish contact with each other, and develop their competences by sharing and building knowledge with other members (Nikiforos *et al.*, 2020). The publication of individual productions and the common achievements of the learners in the VC serve to reinforce group solidarity and raise awareness about the division of work and their responsibility towards the community (Henri and Pudelko, 2003).

2.3. Hypothesis development

We expect that the influence of knowledge-sharing self-efficacy, perceived relative advantage, social identification, and the norm of reciprocity on sharing will vary depending on the type of VC (VC of interest vs. virtual learning community). First, knowledge-sharing self-efficacy may have a stronger influence in a VC of interest than in a virtual learning community. In VCs of interest, the lack of a shared goal makes sharing knowledge in the community voluntary (Hsu *et al.*, 2007; Lin *et al.*, 2009). In VCs where members participate voluntarily, some users are likely to post messages more frequently, whereas others visit the community without posting (Nguyen, 2021). Lai and Chen (2014) found that members who actively shared knowledge were more influenced by knowledge self-efficacy. In contrast, members of virtual learning communities have a common project-based objective, which can encourage the expectation of knowledge sharing within the community (Nguyen, 2021; Nguyen *et al.*, 2019). Thus, whereas knowledge sharing is based on a personal decision in a VC of interest, members in a virtual learning community may feel obligated to share knowledge with others to achieve the common goal (Henri and Pudelko, 2003). Consequently, members who feel confident enough to publish, discuss, and contribute expertise about the topic of interest are more likely to share their knowledge willingly and voluntarily in a VC of interest. Hence, we formulate the following hypothesis:

Hypothesis 1: The influence of knowledge-sharing self-efficacy on knowledge sharing will be stronger in virtual communities of interest than in virtual learning communities.

Second, perceived relative advantage is expected to be more important in a virtual learning community than in a VC of interest. In a virtual learning community, students' academic performance and learning depend on their participation in the community (Huang *et al.*, 2012). Working towards a common educational purpose can motivate members of a virtual learning community to share knowledge within the community, rather than seeking external means of sharing (Karaoglan Yilmaz, 2017). They might also seek to be identified as skilled by the professor, expecting better grades. In VCs of interest, the rewards of sharing knowledge may involve enriching their knowledge, seeking support, and making friends (Lin *et al.*, 2009). However, we argue that achieving the common educational goal in a virtual learning community, along with the motivation for better academic performance, can cause knowledge sharing to be perceived as more beneficial to the individual in this type of community than in a VC of interest. Based on this rationale, we formulate the following hypothesis:

Hypothesis 2: The influence of perceived relative advantage on knowledge sharing will be stronger in virtual learning communities than in virtual communities of interest.

Third, social identification is important in a VC because having stronger feelings of connection with other community members is essential for its survival and success (Han *et al.,* 2020; Luo *et al*. 2021, Shiue *et al.*, 2010). However, social identification with the community is likely to be more important in a virtual learning community than in a VC of interest. Whereas members of a virtual learning community share a superordinate social identity (e.g., academic institution membership) (Ren *et al.*, 2012), members of a VC of interest identify more with the topic than with the other members (Henri and Pudelko, 2003). Moreover, participation in a VC of interest is usually anonymous and voluntary (Shiue *et al.*, 2010), which makes members' emotional attachment weaker (Ren *et al.*, 2012). Therefore, we expect the following:

Hypothesis 3: The influence of social identification with the community on knowledge sharing will be stronger in virtual learning communities than in virtual communities of interest.

Finally, the influence of the norm of reciprocity may be more important for knowledge sharing in virtual learning communities. In large social networks such as VCs of interest, where members are not stable and may not anticipate reciprocal relationships unless they are explicitly stated, the belief that one's effort will be reciprocated by others is weaker (Shiue *et al.*, 2010). However, virtual learning communities are smaller in size, membership is more stable, anonymity is reduced, and a common goal is shared, and so reciprocity might have a stronger effect. Therefore, expecting support or help from others after helping them and feeling indebted for receiving help may encourage knowledge sharing (Huang *et al*., 2020; Luo *et al*., 2021). Based on this rationale, we formulate the following hypothesis:

> *Hypothesis 4*: The influence of the norm of reciprocity on knowledge sharing will be stronger in virtual learning communities than in virtual communities of interest.

In sum, our research model includes knowledge-sharing self-efficacy, social identification, the norm of reciprocity, and perceived relative advantage, all of which influence knowledge sharing. Additionally, the type of VC (VCs of interest and virtual learning communities) functions as a moderator, influencing the strength of the relationships between the other variables. The research model for this study is illustrated in Figure 1.

INSERT FIGURE 1 ABOUT HERE

3. Method

3.1. Sample

A survey methodology was used to collect the data in this study. We posted a link to the questionnaire in various VCs of interest and virtual learning communities. We received a total of 291 responses to the online questionnaire, of which 30 had missing data, leaving us with 261 valid responses. Table 1 summarizes the characteristics of the sample. VCs of interest included several Human Resources-related groups on LinkedIn, groups of Alumni on Facebook and LinkedIn, a forum for young researchers, and a mailing list for au pairs. These communities were open to the public, and data were publicly available. A short message with a hyperlink to our web survey was posted in VCs. In this message, we explained the purpose of the survey (e.g., a research study on knowledge sharing in VCs) and encouraged participation. To ensure members' privacy, the survey did not collect respondents' personal identifying information. Virtual learning communities consisted of four communities of university students; three of them were Facebook groups, and one was a forum. Virtual learning communities had a clear and shared objective among all the participants because they had to develop a project related to their course. These communities were set up by the instructors, who invited students enrolled in an organizational psychology course to join them through a link sent by email. Participation was voluntary, and it was an alternative way to fulfill the practical classes in the course. They had to carry out a collaborative project that consisted of an organizational development proposal for a company. They could post messages, comment on others' posts, upload documents and photos, create short polls, and share links. These communities were monitored by the instructor, who provided feedback on the project and explained the study proposal after their participation ended. Participants filled in an online questionnaire containing the measures of knowledge sharing, knowledge-sharing self-efficacy, perceived relative advantage, social identification, norms of reciprocity, and frequency of visits. The ethics committee approval was obtained for the research project, which was conducted in accordance with the ethical guidelines outlined in the Declaration of Helsinki.

INSERT TABLE I ABOUT HERE

3.2. Measures

Knowledge sharing: This variable refers to participation in knowledge-sharing activities and the time dedicated to them. It was measured with three items from Lin *et al.* (2009). An example of an item is: "I share knowledge in this virtual community". The items were responded to on a five-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree".

Knowledge-sharing self-efficacy: This scale measures the confidence users have in themselves to perform knowledge-sharing actions in a useful manner: publishing, dialoguing, and using different means of expression. It includes six items adapted from Hsu *et al.* (2007). An example of an item is: "How would you rate your level of confidence in yourself about sharing knowledge in the virtual community by offering your ideas and perspectives to others participating in discussions?". The items were responded to on a five-point Likert scale ranging from (1) "very low" to (5) "very high".

Perceived relative advantage: This scale measures the subject's belief that sharing knowledge will help to improve his/her skills or understanding of a topic. It includes three items adapted from Lin *et al.* (2009). An example of an item is: "Sharing knowledge with members of this community will improve my problem-solving capability". The items were responded to on a five-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree".

Social identification: This scale measures the degree of the individual's sense of belonging, togetherness, and positive feelings toward his/her VC. It includes four items adapted from Chiu *et al.* (2006). An example of an item is: "I am proud to be a member of this virtual community". The items were responded to on a five-point Likert scale ranging from (1) "strongly disagree" to (5) "strongly agree".

Norm of reciprocity: This scale measures the degree to which community members expect other community members to share knowledge and help them if they share their knowledge. It contains three items adapted from Kankanhalli et al. (2005). An example of an item is: “When I share knowledge with other community members, I am convinced that they will help me if I need it”. The items were responded to on a five-point Likert scale ranging from (1) “strongly disagree” to (5) “strongly agree”.

Frequency of visits to the VC is used as a control variable in this study, in order to avoid overestimating the influence of the independent variables in the analyses. Respondents were asked about the number of times per week they usually visit the VC. There were five possible choices: “less than once a week”, “once a week”, “several times a week”, “once a day”, and “several times a day”.

3.3. Data analysis

Before conducting hypothesis testing, we evaluated both reliability and construct validity. For reliability, we calculated the Composite Reliability (CR). To assess convergent and discriminant validity, we computed the Average Variance Extracted (AVE) and the Heterotrait-Monotrait ratio of correlations (HTMT). Specifically, we used HTMT2 (Jorgensen *et al*., 2022) because it provides a more consistent measure for congeneric measurement models (Roemer *et al*., 2021). Finally, given that all the data were collected from self-reports, we examined the potential for common method variance.

The statistical analyses of the present study were performed using RStudio for Windows (Posit team, 2024). More concretely, structural equation modeling was used with the lavaan package in R (Rosseel, 2012). A multi-group model was calculated to compare the influence of the independent variables on knowledge sharing in the two types of VCs examined in the present study (VCs of interest and virtual learning communities). We used a chi-squared difference test to compare a fully unconstrained multi-group model with a model with a specific constrained path. This was done one by one for all the paths, making it possible to test for moderation in each specific relationship (Hair *et al.*, 2010). Additionally, goodness-of-fit of the models was tested following the cut-off criteria of a comparative fit index (CFI) greater than 0.95, a root mean squared error of approximation (RMSEA) equal to 0.06 or less, and a standardized root mean squared residual (SRMR) equal to 0.08 or less (Hu and Bentler, 1999).

4. Results

4.1. Reliability and construct validity

An assessment of the normality of all the variables shows skewness and kurtosis within the accepted boundaries of -2 and +2 (George and Mallery, 2016). Results of the homoscedasticity test scatter plot indicate that all the variables are homoscedastic. We tested the Variable Inflation Factor (VIF) for all the exogenous variables simultaneously, obtaining a VIF of less than 2.0 for all variables, which indicates that there are no multicollinearity problems (Hair *et al.*, 2010).

The reliability and construct validity of all the constructs were tested by means of confirmatory factor analysis. We used Robust Maximum Likelihood as the estimation method. Regarding the measurement model, the model showed an adequate fit ($\chi^2_{(142)}$= 179.267; CFI= .981; SRMR= .040; RMSEA= .032). The reliability and validity indices for all measures appear in Table 2. The CR for all measures was above the threshold of 0.7.

Moreover, we calculated the AVE and HTMT2 to assess convergent and discriminant validity. The AVE values for all constructs were satisfactory, exceeding the 0.5 threshold, thus supporting convergent validity (Fornell and Larcker, 1981) (see Table 2). To evaluate discriminant validity, we compared the HTMT2 values to the recommended threshold of 0.85, below which discriminant validity is considered acceptable (Henseler *et al*., 2015). As Table 3 shows, all the HTMT2 values fell below this threshold, indicating good discriminant validity for the constructs.

INSERT TABLE II ABOUT HERE

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Independent and dependent variables were collected with a single questionnaire. Therefore, we conducted a common method bias test. The "unmeasured latent factor" method was employed (Podsakoff *et al*., 2003), which involves comparing standardized regression weights for all items before and after adding a common latent factor. Our results indicate that none of the regression weights were substantially affected by this common latent factor, with differences of less than 0.2 for all items. This result suggests that the variations were negligible, and that common method bias is not a concern in our study.

4.2. Hypothesis testing

The research hypotheses predicted that the type of VC would moderate the relationships between the independent and dependent variables. Prior to the moderation analysis, it is necessary to test for measurement invariance in order to ensure the equivalence of the measurement instruments across both groups of the moderator variable. This procedure tests for configural and metric invariance (Hair *et al.*, 2010). First, the test for configural invariance verifies that the factor structure of the measurement model is applicable to both groups of the moderator. To do so, a completely free multiple group model was estimated for both groups of the moderator (Model 1). The model remains freely estimated; all parameters are set free to vary across groups. Second, the test for metric invariance involved developing a model (Model 2) with factor loadings constrained to be equivalent across groups. Finally, Model 2 was compared to Model 1 to test for metric invariance.

Model fit for Model 1 was: $\chi^2_{(284)} = 372.325$; CFI= .960; RMSEA= .053, and for Model 2: $\chi^2_{(298)} = 390.295$; CFI= .958; RMSEA= .053. The results for the chi-squared test comparing Model 1 and Model 2 ($\Delta\chi2 = 17.937$; $\Delta DF= 14$; $p > .05$) indicated that full metric invariance was satisfied. Furthermore, according to Chen (2007), when the RMSEA increases by less than .015, one can claim support for the more constrained (parsimonious) model. Cheung and Rensvold (2002) suggested that decreases in fit greater than .01 in the CFI might be important. Our results showed changes smaller than 0.01 (ΔCFI=.002; ΔRMSEA=.000), which suggests that metric invariance is supported. Therefore, it was possible to proceed with further testing.

Moderation was tested by creating a multi-group path model. The results are shown in Table 4. Hypothesis 1 predicted a moderator role of the type of VC in the relationship between knowledge-sharing self-efficacy and knowledge sharing. We found that this relationship was stronger in VCs of interest ($b=.500$, $p<.01$) than in virtual learning communities ($b=.166$, $p>.05$) ($\Delta X^2=4.046$, $\Delta DF=1$, $p<.05$). Thus, Hypothesis 1 was supported.

Regarding Hypothesis 2, related to the perceived relative advantage-knowledge sharing relationship, a moderation effect of the type of VC was found ($\Delta X^2=8.041$, $\Delta DF=1$, $p<.01$). Perceived relative advantage has a significantly stronger influence on knowledge sharing in virtual learning communities ($b=.330$, $p<.01$) than in VCs of interest ($b=-.099$, $p>.05$). Thus, Hypothesis 2 was supported.

According to Hypothesis 3, we expected a moderator role of the type of VC in the relationship between social identification and knowledge sharing, so that this relationship would be stronger in virtual learning communities. The results show that the type of VC does not moderate the relationship between social identification and knowledge sharing ($\Delta X^2=.072$, $\Delta DF=1$, $p>.05$), indicating that this hypothesis was not supported.

Finally, Hypothesis 4 is not supported, indicating that the type of VC does not moderate the norm of reciprocity-knowledge sharing relationship ($\Delta X^2=.960$, $\Delta DF=1$, $p>.05$).

INSERT TABLE IV ABOUT HERE

5. Discussion

The impact of personal and contextual factors on knowledge sharing in VCs has been widely studied (Hernández-Soto et al., 2021; Fauzi, 2019; Nguyen, 2021; Nguyen et al., 2019; Zhao et al., 2022). However, the influence of the type of VC has been overlooked. Thus, the aim of the present study was to increase the understanding of the role played by the type of VC by comparing two types of VCs: VCs of interest and virtual learning communities. For this purpose, we focused on the personal factors of knowledge-sharing self-efficacy and perceived relative advantage, as well as the contextual-relational factors of social identification and the norm of reciprocity. We review and discuss our results in the following paragraphs.

As expected, the influence of self-efficacy on knowledge sharing was stronger in VCs of interest than in virtual learning communities, supporting our first hypothesis. Thus, this result points out that those who feel capable of engaging with others in discussions, writing responses, and using their communities' tools to answer questions or add knowledge are more likely to contribute to the community in a VC of interest than in a virtual learning community. This result can be attributed to the differences between VCs of interest and virtual learning communities. In a VC of interest, knowledge sharing is voluntary, and individuals are motivated to fulfill their own personal objectives by engaging in exchanges and building relationships with others within the community (Chou and Hung, 2016; Hsu *et al.*, 2007; Lin *et al.*, 2009). However, in a virtual learning community, knowledge sharing can be viewed as a public good, something that belongs to all, affects everyone, and has to be maintained by the community. In this context, sharing may be seen not only as a way to fulfil individual self-interest, but also as a collective commitment (Luo *et al.*, 2021). Moreover, the fact that members of our virtual learning communities knew each other from class and had prior work experience, along with the requirement of developing a project in a specific time frame within the community, could reduce the importance of self-efficacy for knowledge sharing.

Regarding the second hypothesis, our results provide support for the moderating role of the type of VC between perceived relative advantage and knowledge sharing. As expected, the main goals of learning and academic performance can cause sharing knowledge in a virtual learning community to be perceived as more beneficial, which in turn motivates its members to share more knowledge in the community (Huang *et al.*, 2012; Karaoglan Yilmaz, 2017). However, this relationship was not significant in VCs of interest. A possible explanation is that, in these communities, individuals join to become more knowledgeable about the topic, without expecting other gains in return, which might make extrinsic motivators less relevant (Nonnecke *et al.*, 2006). Thus, the perceived relative advantage participants can obtain from sharing knowledge with the community is more important in a virtual learning community than in a VC of interest.

Our results show that the type of community does not moderate the relationship between social identification and knowledge sharing (Hypothesis 3). Although we expected that this relationship would be stronger in virtual learning communities (due to the existence of a supraordinate identity shared by members and shared goals), the effect size of this relationship was quite similar in both types of VCs. This finding points out that developing a shared identity with the community is an important motivator for knowledge sharing, regardless of the type of community, perhaps because social identity is based on the collective characteristics of the VC. However, members' attachment to the community is not only based on social identity, but also on interpersonal bonds (Karaoglan Yilmaz, 2017; Ren *et al.,* 2012). Thus, considering this difference, it would be worthwhile to examine whether interpersonal bonds may behave differently depending on the type of VC. The attention is shifted from the VC as a whole (i.e., social identity) to the particular characteristics of individual members, and the type of VC may condition the extent to which members can develop stronger interpersonal bonds.

Lastly, the type of community does not moderate the relationship between the norm of reciprocity and knowledge sharing (Hypothesis 4). Although reciprocity was not a significant determinant of knowledge sharing in either VC, previous research has shown that the effect of reciprocity might be mediated by other factors, such as trust (Lin *et al.*, 2009). Trust smooths relationship building between members (Kang *et al.*, 2016; Lin *et al.*, 2009). Another explanation is that the exchanges in VCs tend to be generalized rather than dyadic, which makes reciprocity unnecessary for collective action (Feng and Ye, 2016; Wasko and Faraj, 2005).

Although this study offers valuable insights about knowledge sharing, it has some limitations. First, it is a cross-sectional study, which only allows us to capture participants' perceptions at one point in time. However, by taking a longitudinal approach, future research could adopt a more comprehensive approach to studying several stages of VC development. Second, several statistical analyses were conducted to reduce (e.g., a common method bias test, using an unmeasured latent factor), but not eliminate, the issue of common method variance (Podsakoff *et al.*, 2003). The results of these statistical tests showed that the study had good internal validity to reduce the threat of common method variance. Considering different types of data, such as social network metrics, will enable future researchers to analyze members' behaviors and address different types of communities in order to better understand the role of the type of community in knowledge sharing. Third, virtual environments are constantly evolving, with new technologies significantly influencing their development. As mentioned in the introduction, generative AI has the potential to transform the way knowledge is created and managed within VCs, which is a potential direction for future research that should be further examined. Fourth, this study explored the impact of personal and contextual factors on knowledge sharing in two specific types of VCs.

This focus may limit the generalizability of our findings to other community types, particularly those that are less goal-oriented, such as relationship-based virtual communities or communities of practice. Finally, our research did not examine two important aspects of knowledge sharing. The first aspect is knowledge quality (Dzenopoljac *et al.*, 2024), which is increasingly critical given the rise of misinformation online and the demand for reliable information. Although we focused on whether members of VCs shared knowledge, we did not assess how this knowledge is perceived in terms of usefulness and quality. Higher-quality shared knowledge adds greater value to the community than a mere accumulation of information. The second aspect is the distinction between tacit and explicit knowledge (Abidi *et al.*, 2023). Tacit knowledge enhances the overall quality of shared knowledge (Dzenopoljac *et al.*, 2024), making it essential to explore the extent to which tacit knowledge is shared in VCs. By establishing metrics for knowledge quality and examining the sharing of tacit knowledge, future research can provide deeper insights into the value of knowledge in VCs.

6. Conclusion

6.1. Theoretical implications

This study underscores the significant role the type of VC plays in shaping knowledge sharing in online environments. Previous research indicates that personal factors and the characteristics of online environments influence knowledge sharing (Chang and Chuang, 2011; Chen and Hung, 2010; Ergün and Avcı, 2018; Fauzi, 2019; Fauzi *et al.*, 2023; Lin et al., 2009; Wang, J. *et al.*, 2019; Ye *et al.*, 2015). However, our study provides new evidence about the moderating role of the type of VC, emphasizing the importance of VC characteristics in understanding how personal and contextual factors impact knowledge sharing. Specifically, self-efficacy is more important for knowledge sharing in VCs of interest, whereas perceived relative advantage has greater significance in virtual learning communities. We also found that social identification and norm of reciprocity are equally important in VCs of interest and virtual learning communities. Therefore, our findings contribute to the existing literature by highlighting the need for a more comprehensive approach to studying knowledge sharing in VCs, one that considers the differences among various types of communities. By examining personal and contextual factors across different VCs, our research enhances the understanding about which specific variables are critical for knowledge sharing in VCs. The identification of relevant antecedent factors contributes to advancing the field of information and knowledge management online. Finally, our study extends Social Exchange Theory (Blau, 1964) and responds to previous calls for research on the specific variables that influence online knowledge sharing (e.g., Hernández-Soto *et al*., 2021; Karaoglan Yilmaz, 2017; Luo *et al*., 2020; Ye *et al*., 2015; Zhao *et al*., 2022).

6.2. Practical implications

Our results have practical implications for community managers and instructors. Community managers should consider the type of community and its characteristics when devising a strategy to encourage members to contribute to the VC. In VCs of interest, managers should provide guidelines and training programs, along with technical support to help participants improve their knowledge-sharing self-efficacy (Lin *et al*., 2009), because this variable fosters their participation in the VC. In virtual learning communities, instructors should try to improve the perceived relative advantage. To do so, some strategies would involve providing information about the benefits of participating in the community and trying to improve the community's reputation (Lin *et al.*, 2009). For instance, the expectation that the community can give reasonable rewards and timely recognition for contributions can make members more inclined to contribute (Dong *et al.*, 2020). Finally, it is useful to contemplate strategies that foster social identification in either type of VC. Managers and instructors can emphasize the community's purpose and make the VC's group attributes more salient in order to improve members' identification and attachment to the community (Ren *et al.*, 2012).

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Figure captions

Figure 1. Research model

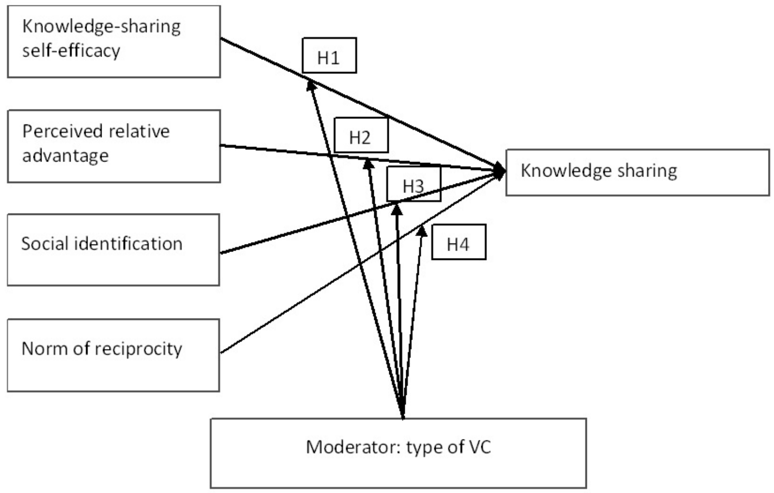

Figure 1. Research model

225x113mm (120 x 120 DPI)

Table I. Demographic information of the sample

Measure	Items	Frequency		Measure	Items	Frequency	
Age	20 Below	8	3.07%	Sex	Female	174	66.67%
	21-30	193	73.95%		Male	87	33.33%
	31-50	51	19.54%	Frequency visiting	Less than once per week	22	8.43%
	50 Above	9	3.45%		Once per Week	43	16.48%
					Several per week	60	22.99%
					Once per day	53	20.31%
Occupation	Employed	79	30.27%		Several per day	83	31.80%
	Unemployed	15	5.75%				
	Student	167	63.98%	Education	PhD	24	9.20%
					University graduate	57	21.84%
Type of VC	Interest	148	56.70%		University student	147	56.32%
	Learners’	113	43.30%		High School	33	12.64%

Table II. Item relevant statistics, reliability and validity indices.

Measured items	Item to total correlation	Factor loading (standardized)	CR	AVE
KSB			0.750	0.501
KSB01	0.589	0.775***		
KSB02	0.579	0.684***		
KSB03	0.586	0.670***		
KSE			0.889	0.573
KSE01	0.726	0.782***		
KSE02	0.704	0.754***		
KSE03	0.734	0.787***		
KSE04	0.725	0.785***		
KSE05	0.642	0.675***		
KSE06	0.701	0.752***		
SI			0.889	0.671
SI01	0.761	0.852***		
SI02	0.804	0.890***		
SI03	0.768	0.796***		
SI04	0.673	0.706***		
PRA			0.859	0.670
PRA01	0.713	0.798***		
PRA02	0.740	0.825***		
PRA03	0.744	0.833***		

NR			0.810	0.592
NR01	0.584	0.661***		
NR02	0.712	0.863***		
NR03	0.672	0.788***		

Note: *** $p < 0.001$; KS: knowledge sharing; KSE: Knowledge-sharing self-efficacy; SI: Social identification; PRA: Perceived relative advantage; NR: Norm of reciprocity.

Table III. Means, standard deviations, and Heterotrait-monotrait (HTMT2) ratio of correlations

	Mean	SD	KS	KSE	SI	PRA	NR
KS	3.265	0.826	1				
KSE	3.575	0.727	0.568	1			
SI	3.273	0.894	0.552	0.449	1		
PRA	3.417	0.916	0.473	0.432	0.662	1	
NR	3.572	0.796	0.517	0.446	0.731	0.671	1

Note: KS: knowledge sharing; KSE: Knowledge-sharing self-efficacy; SI: Social identification; PRA: Perceived relative advantage; NR: Norm of reciprocity.

Table IV. Moderation Effects

Constrained path	Unstandardized coefficient	Constrained model		χ^2 difference test		
		χ^2	DF	$\Delta\chi^2$	ΔDF	Sig
KSE→KS		452.466	321	4.046	1	< 0.05
VCoI	0.500**	—	—	—	—	—
VLC	0.166	—	—	—	—	—
SI→ KS		448.088	321	0.072	1	NS
VCoI	0.274*	—	—	—	—	—
VLC	0.274*	—	—	—	—	—
PRA→ KS		454.508	321	8.041	1	<0.01
VCoI	-0.099	—	—	—	—	—
VLC	0.330**	—	—	—	—	—
NR→KS		449.466	321	0.960	1	NS
VCoI	-0.070	—	—	—	—	—
VLC	-0.070	—	—	—	—	—

Note: * $p < 0.05$, ** $p < 0.01$.

The chi-square for the unconstrained model was: 448.427; DF= 320.

KS: knowledge sharing; KSE: Knowledge-sharing self-efficacy; SI: Social identification; PRA: Perceived relative advantage; NR: Norm of reciprocity; VcoI: Virtual community of interest; VLC: Virtual learning community.