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Significant and hierarchy of variables affecting online knowledge-sharing using an integrated logit-ISM analysis

Jihe Chen[1,2] · Ying Zhou[1] · Litian Lv[3]

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Abstract
This study aims to explore the significant variables affecting online knowledge-sharing and the hierarchical structure, from the perspective of online learners. To comprehensively discuss the relationship between these variables, binary logit regression and interpretative structural model (ISM) was used. Based on literature analysis, the data of 29 candidates were obtained, and 670 valid data was acquired through an electronic questionnaire. A total of 13 significant variables were also obtained using the Logit model of SPSS 22, with an 8-layer ISM program established by MATLAB 2017A software. The results showed that six of the 13 variables had positive effects on online knowledge-sharing behavior, with the remaining seven having a negative impact. The ISM model also proved that trust and delete/block, reward, and the remaining elements were shallow, deep, and intermediate variables, respectively. Combining the Logit and ISM advantages, these results strengthened the reports on online knowledge-sharing behavior, subsequently obtaining five suggestions for its development. This study is expected to help teachers and online course developers design better digital programs, as well as ensure the accurate decision-making of students in knowledge sharing activities.

Keywords Online knowledge sharing · Logit · Interpretative structural model · Hierarchical structure

✉ Ying Zhou
zhouying66@mailbox.gxnu.edu.cn

✉ Litian Lv
1875157420@qq.com.com

Jihe Chen
1113952796@qq.com.com

1 Department Mathematics and Statistics, Guangxi Normal University, Guilin, China

2 New Century School, Guangdong, China

3 College of Environment and Resources, Guangxi Normal University, Guilin, China

1 Introduction

Online learning has become an important method of obtaining educational resources, exchanging academic ideas, and knowledge sharing, through the development of virtual, 5 g, and other emerging technologies (Sun, 2021; Xu et al., 2019). In this condition, the pattern of learning was higher than the traditional type, as teachers and students do not need to study synchronously (Liu Ting, 2019). Digital platforms such as MOOC, Stanford online, and Khan Academy, are also active with large users, causing a variety of multitasking activities (Zhang et al., 2015). This shows that learners often acquire the knowledge they need anytime and anywhere through these online platforms, which promotes global information exchange and cross-regional cooperative learning during the Covid-19 pandemic, this technical learning process was observed to have gradually replaced traditional teaching (Akour et al., 2021). When the frequency of online learning increases, the synergy between media is more obvious, as people are willing to digitally socialize, consume, and seek jobs (Dong et al., 2018). Social networking sites such as Facebook, Twitter and Weibo, are also commonly used to communicate, exchange and share knowledge, opinions, and ideas, as well as encourage continuous member interactions (Cinelli et al., 2020; Fazel et al., 2021; Hussain et al., 2021; Li et al., 2020). In the digital information exchange mechanism, online knowledge sharing has become an important communication channel. By asking and answering questions (Q&A), people began to seek help and share their learning methods with other users (Osatuyi et al., 2022). Based on the communication function of social networks, the facilitation of people became possible and necessary in conducting numerous activities, such as dialogue and knowledge sharing, helping individuals and organizations to establish more learning connections, as well as enhancing knowledge transmission and updates. This indicates that more content sharing leads to greater reward acquisition (Anand & Walsh, 2016). The sharing process also helps to seek or provide assistance from/for others, due to being a behavior worth promoting in the present evolving information society (Feng et al., 2021). Irrespective of these conditions, some risks are still worthy of consideration in online media, such as information leakage, low knowledge-sharing quality, and the avoidance of expanding competitive relationships, which promotes the reluctance of people to evaluate or share their situations.

Since some studies explored the factors affecting this online process, most of them were found to emphasize the impact of social media on users' behavior or developed structural equation models around these variables, such as knowledge sharing and self-efficacy, social presence, academic performance, and technology perception (Ahmed et al., 2019; Zuo et al., 2021). A lack of comprehensive and hierarchical assessments was still not studied irrespective of these reviews. This was in line with the inadequate perceptions on the logical relationship and hierarchical structure between various variables. Therefore, this study aims to explore the variables affecting online knowledge sharing, based on the perspective of digital learners. The significance of this report is to determine and distinguish the salient factors influencing these processes according to their variability levels, i.e., either deep (fundamental) or shallow (direct). This result is expected to help teachers and online course developers design better online programs, as well as ensure the accurate decision-making of students in knowledge sharing activities.

2 Literature reviews

2.1 Online knowledge sharing

This is an act of exchanging information among users (Bock et al., 2005), where knowledge sharing plays an important role in skill diffusion, proficiency update, and teamwork ability improvements (Alsharo et al., 2017). It also helps to accelerate systematic learning innovation and collaborative education enhancement (Sita Nirmala Kumaraswamy & Chitale, 2012). Using social media, this behavioral process helps to improve users' co-creation significance, including customer learning, social integrative, and hedonic values (Chen et al., 2017). This indicates that online knowledge sharing is very helpful for both individuals and teams. Virtual communities and learning platforms also provide users with more opportunities for this behavioral process, where people effectively interact and develop relationships. This shared knowledge is likely observed as a general or professional proficiency, personal experience, and other information. Besides, it also exists as Q&A in the online platform (Deng et al., 2018). According to Hwang, online knowledge sharing was defined as voluntary individual actions in asking and answering questions within a virtual community platform, to exchange proficiency (Hwang et al., 2015). In this condition, the sharing behavior of college students occurred in the learning and communication of online courses, as well as the use of social media, where they actively ask their classmates and teachers their questions or answer other people (Arif et al., 2022; Charband & Jafari Navimipour, 2018). Therefore, this study defines online knowledge sharing as the distribution of perceptions, answering to others, or obtaining learning-based information on digital courses' software and social media, such as MOOC, Wechat, etc.

2.2 Online knowledge sharing and online education

The COVID-19 pandemic has been reportedly to have a huge impact on the global educational sector, where online learning became the main form of the system under the broad emergency response policy (Cotoman et al., 2022). Compared to the traditional system, this learning process is more attractive regarding the provision of multiple digital media technologies, including social networking platforms (Patterson, 2017). This led to the satisfaction of students with the digital knowledge-sharing effect (MUZAMMIL et al., 2020). According to Lin and HF, the Fuzzy-AHP method was used to analyze the relative weights of 16 attributes affecting knowledge sharing, where a preliminary model was objectively and quantitatively obtained (Lin et al., 2009). Casimir also stated that shared knowledge was affected by the relationship between emotional trust and commitment, as well as sharing the cost. The results showed that stronger group relationship trust led to the greater will of people to participate in knowledge sharing (Casimir et al., 2012). Furthermore, online learning provides opportunities for cross-cultural exchange and international collaborative education (Hajhashemi et al., 2017). In the virtual network environment, the speed of cross-border knowledge dissemination has been greatly improved, with sharing trust and engagement providing a special emotional exchange for course learning and higher connection. Irrespective of these conditions, the lack of constant internet connection and adequate teaching resources promoted the negative reactions to students' online learning performance and the reluctance to participate in online knowledge sharing (Agormedah et al., 2020; Ates Cobanoglu & Cobanoglu, 2021). The adaptation pattern of the course content to the needs and preferences of learners is also an issue that needs to be considered in the development of this sharing process (Gyamfi & Sukseemuang, 2018).

2.3 Online knowledge sharing and technical security

One of the potential threats to the present online knowledge sharing is the leakage of personal information due to technical problems or cyber violence, which destroys the digital learning and communication environment (Pidgeon et al., 2013). Based on the specific and unique personalities from different cultural backgrounds, people's willingness to share information should be encouraged and adopted, due to being an act of kindness on many social occasions, shopping guides, policy reviews, etc. (Markus & Kitayama, 1991). Anonymous virtual learning communities also need to protect private information, for the sharers to be noticed by others according to their shared knowledge. This should not be performed because of their name or private information, such as country and religion. In this condition, students are likely to hide their identities when they are uncomfortable during knowledge dissemination (Chang, 2021).

2.4 Online knowledge sharing and value attraction

Based on Diah, factors such as transparency and content quality had an impact on an organization's value co-creation (Priharsari & Abedin, 2021). This showed that knowledge sharing created new value and strengthened social relation connections when an adequate response was obtained in the virtual community. In this condition, a value judgment was invisibly formed, i.e., people were more inclined to agree with a specific perception. The literature also stated that valuable knowledge sharing enhanced people's trust in a virtual community (Chai & Kim, 2010). Assuming that the knowledge shared by an individual is recognized by the majority of people, the sharer is likely to attract the attention of others, with the content being observed as a valuable contribution. In addition, social connections and reputation were found to significantly affect a person's social behavior (Wasko & Faraj, 2005). This proved that people often share information and knowledge through shared URLs or private

IDs when an opportunity to expand their influence is observed. In this case, social media such as Facebook, Twitter, YouTube, etc., were often active with many private IDs or individual organizations, which used these platforms to share influential videos or links, towards the acquisition of more followers (Brombin et al., 2021).

2.5 Online knowledge sharing and cooperative learning

Extensive social media network provides technical solutions and opportunities for people to establish cooperative learning. In this condition, users are found to also establish online sharing knowledge links and disseminate useful learning tools such as registering Facebook groups (Nguyen et al., 2013), WhatsApp (Martínez-Comeche & Ruthven, 2021), and Road-mapping (Krull et al., 2022). This is often accompanied by the invitation of classmates, friends and colleagues to participate in the construction of knowledge. While expanding cooperation and exchanges, they also share their ideas and improve the development of specific knowledge through collective strength. According to a qualitative analysis study, students expressed a preference for capitalizing on the opportunities provided by knowledge sharing technology (Ozdamli & Cavus, 2021). The results confirmed that all members collectively influenced the development process of the project through interaction and cooperation, to improve the overall structure and nature of the work. In this case, everyone contributed to the project, achieved clustered partnerships, and actualized close emotional exchanges between members, ensuring the valuable status of the work.

Based on these assessments, online knowledge sharing became more important in various aspects, such as digital education, learning benefits, personal value enhancement, network security, and cooperative relationship establishment. Irrespective of these conditions, many issues still need to be considered, such as the role of individual factors, sharing motivation, technology application and privacy security variables. It also has important guiding significance and practical value through the determination of the hierarchical structure, to intuitively display the logical relationship and importance degree among variables.

3 Theoretical background and variables' selection

3.1 Social exchange theory

This explains that social behavior is the process of exchanging information (Gouldner, 1960), with knowledge sharing being the distribution of information, skills or expertise between different public groups (Charband & Jafari Navimipour, 2016). In this condition, people's engagement motivations in communication are closely related to maximizing benefits and minimizing costs. People also weigh the potential benefits and risks of online knowledge sharing and quit when the uncertainties outweigh the rewards (Surma, 2016). Meanwhile, they participate in virtual communities to exchange information when the benefits exceed the perceived risks. Social exchange theory also explains the behavior of online knowledge sharing, where repetition of the mastered information is observed during network dissemination (Hall et al., 2010). This behavior is accompanied by the different influential degrees of external incentive variables, social-psychological forces, and discussion atmosphere on knowledge sharing willingness. When members intensively interact and trust each other, they tend to share reliable knowledge. In this case, the members with perceived fairness, experience, and similar language, are likely to provide more high-quality knowledge (Chang & Chuang, 2011). Furthermore, the individual's learning ability, as well as social trust and interaction significantly affected knowledge sharing behavior, with shared concepts and collectivism having moderating effects on the public factors (social trust and interaction) (Nguyen, et al., 2022a, 2022b). This confirms that the sharing behavior is an effective carrier of trust and interaction in social exchange, due to playing an important role in promoting public information communication.

3.2 Technology acceptance model

This model believes that people's behavior in selecting a specific product is determined by behavioral Intention (BI) (Davis et al., 1989), with BI being developed by attitude and perceived usefulness (BI = A + U) (P. Surendran, 2012). Based on these assessments, the use of technology and perceptual techniques play an increasingly important role in people's online education, shopping, and communication. According to Al-fraihat, a PLS-SEM model was established to verify the impact of fusion technology education on e-learning satisfaction (Al-Fraihat et al., 2020). In the projects related to technical variables, the three predictive factors affecting teamwork and business training sharing behavior includes enjoyment, belonging, and attitude (da Silva et al., 2022). Informal associations and task dependencies also contribute to the establishment of knowledge sharing relationships (Liu et al., 2022). Moreover, virtual identity and knowledge creation self-efficacies have significant predictive effects on sharing behavior (Kim et al., 2020). This is in line with knowledge acquisition and sharing, where significant positive effects are observed on perceived usefulness and ease of use (Al-Emran & Teo, 2020), which supports the following hypothesis,

> "There is a significant influence relationship between online knowledge sharing and technology use".

To reduce the risk of privacy disclosure in this online process, students' products should be considered in knowledge sharing activities. This indicates that students are eligible to hide their identities when uncomfortable with public dissemination (Chang, 2021).

3.3 Theoretical summary

In the acquisition or distribution of information, the knowledge sharing capabilities of online communities have become more extensive (Hwang et al., 2015).

This shows that knowledge exchange and technology use have a dynamic effect on individuals' willingness to participate in the online process. The integration of these elements also categorized knowledge sharing in two different forms, i.e., scattered and aggregated (Zagalsky et al., 2018). According to Tausczik, several influential factors of the sharing behavior were summarized, such as Technology, Motivation and Individual differences, as well as Group dynamics, which all involved information exchange and technological use (Tausczik & Huang, 2020). This proved that online knowledge sharing obtained attention from both social exchange theory and technology acceptance model (TAM). The influential variables also contained information exchange theory and are closely related to the support of TAM. Meanwhile, social exchange theory showed that reciprocal exchange relations are realized through trust and orderly interaction (Molm et al., 2000). The provision of more high-quality social media sharing also helped to generate more revenue from other members (Szymczak et al., 2016), with the utilization of technology improving students' willingness to use electronic platforms through TAM (Natasia et al., 2022). In addition, the perceived ease of use and usefulness, as well as social presence influenced people's intention to create and share knowledge (Allam et al., 2020), leading to the following hypothesis (Wu et al., 2016),

"The use of the system help students acquire and share knowledge".

Based on this analysis, the relationship between social exchange theory, online knowledge sharing, and the technology acceptance model is summarized in Fig. 1.

In Fig. 1, online knowledge sharing was observed as a combination of social exchange and technology use. This showed that sharing is a small social exchange process where technology plays a moderating role and enhances individual dissemination behavior (Liu et al., 2011). It was also related to the individual, motivational, environmental and technological factors of sharers (Tausczik & Huang, 2020; Wang & Noe, 2010). Before the decision to digitally share knowledge,

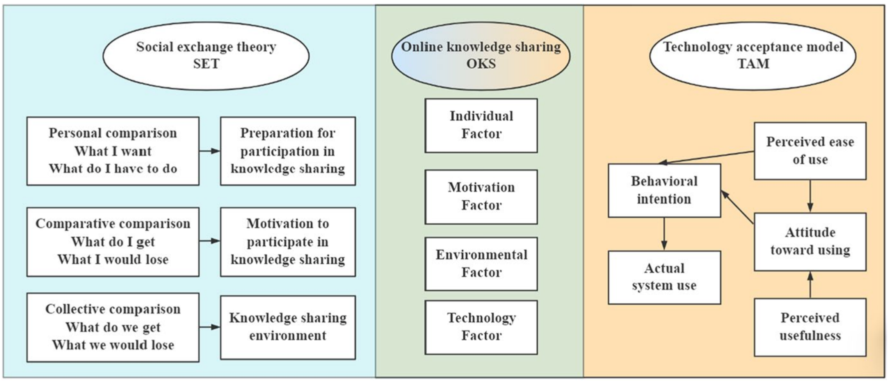


Fig. 1 Relationship between SET, OKS and TAM

people often consider various factors, including the personal participation aim, the sharing motivation and environment (Nguyen, 2019), as well as the benefit and price measurements. The potential prices include the time, knowledge, cognitive, and technology costs (Yan et al., 2016), with the benefits containing self-efficacy, reputation, and reciprocity (Nguyen et al., 2022a, 2022b).

3.4 Variable selection

Based on a literature review, the variables such as individual characteristics and subjective willingness to share, objective environmental perception, and technological application, were found to have an impact on the dissemination behavior of online learning. This was carried out by synthesizing the perspectives of social exchange and technology acceptance theories. To integrate the variables at different levels, the following were selected as the primary indicators influencing online knowledge, namely the individual perspective, participation motivation, as well as environmental and technology perceptions. In addition, a total of 29 variables were selected as the secondary indicators, such as gender and education (Table 1).

4 Methods and results

4.1 Study methods

In the knowledge sharing activities, the willingness to participate was assumed as an obvious binary variable. Based on Table 1, the binary Logit regression was initially used to screen out the variables with significant influence on the sharing process. This was accompanied by the analysis of their hierarchical relationship through ISM, to obtain the final structure.

4.1.1 Binary Logit regression

Binary Logit regression is a common statistical probabilistic nonlinear model used to study the relationship between dichotomous observations y and some influential variables $(x_1, x_2, \ldots, x_n)$. For example, medical patients are often judged by their symptoms (Babiker et al., 2021), identify the variables triggering traffic hazards (Samerei et al., 2021), and the teaching pattern of college teachers (Saha et al., 2022).

Consider the vector set, $x = (x_1, x_2, \ldots, x_n)$, containing n independent variables, and let the conditional probability, $P(y = 1|x) = p$, be the occurrence of an event, x, according to the observed quantity. Subsequently, the Logit regression model is expressed as follows:

Table 1 The name of the variable and its source

N	I	II	References
X1	Individual variable (IV)	Sex	(Akosile & Olatokun, 2020)
X2		Age(Real age)	(Chang et al., 2018)
X3		Grade	(Eid & Nuhu, 2011)
X4		Weekly time on online learning	(Zhang et al., 2021a, 2021b)
X5		Daily time spent on social media	(Charband & Jafari Navimipour, 2016)
X6		Own knowledge reserve	(Song et al., 2021)
X7		Learning style independent or cooperative	(Liu, 2020)
X8	Motivation variable (MV)	Social presence	(Hamid et al., 2015)
X9		Improve self-worth/reputation	(Hosen et al., 2021)
X10		Learning more knowledge	(Jeon & Lee, 2020)
X11		Need the help of others	(Chatterjee et al., 2020)
X12		To help others	(Stewart & Gosain, 2006)
X13		Establish cooperative relationship	(Dmitrii Doronin et al., 2021)
X14		Be encouraged or recognized by others	(Moghavvemi et al., 2017)
X15		Enjoy entertainment or relaxing	(Cheung & Lee, 2009)
X16	Environmental variable (EV)	The relevance of knowledge sharing content and curriculum learning	(Gamlath & Wilson, 2020)
X17		Quality of knowledge sharing	(Dimitry Doronin et al., 2020)
X18		The content of knowledge sharing is trustworthy	(Kim & Park, 2021)
X19		The language/culture of knowledge sharing	(Al-Husseini, 2021)
X20		Reward mechanism	(Lombardi et al., 2020)
X21		A common learning environment	(Lai et al., 2020)
X22		Knowledge sharing gets a response	(Hafeez et al., 2019)
X23		Atmosphere of knowledge sharing	(Lo & Tian, 2020)

Table 1 (continued)

N	I	II	References
X24	Technical variable (TV)	Access common resources	(Eid & Al-Jabri, 2016)
X25		Privacy Security	(Wu, 2020)
X26		Push knowledge that may be interest	(Manoharan & Senthilkumar, 2020)
X27		Delete or block information	(Leonardi, 2014)
X28		Convenient operating system	(Salloum et al., 2019)
X29		Adequate hardware and software resources	(Jacques et al., 2021)

$$\ln\left(\frac{p}{1-p}\right) = g(x) = w_0 + w_1x_1 + \ldots + w_nx_n \quad (1)$$

The established Logit model is then shown as follows:

$$KS_i = w_0 + w_{1\alpha}IV_{1\alpha} + w_{2\beta}MV_{2\beta} + w_{3\chi}EV_{3\chi} + w_{4\delta}TV_{4\delta} \quad (2)$$

where, IV, MV, EV, and TV = individual, motivation, environmental, and technical variables, respectively (Table 1), $i = 1, 2, \ldots, 660; \alpha, \beta = 1, 2, \ldots, 7; \chi = 1, 2, \ldots, 9; \delta = 1, 2, \ldots, 6.$

4.1.2 The ISM Model

The Interpretative Structural Modeling (ISM) method is a widely used systematic scientific model (Warfield, 1974). It is derived from SM (Structural Modeling), which initially divides the analyzed system into various subsystems (variables or elements) through sorting. This is then accompanied by the analysis of the variables and their relationships. These are subsequently mapped to a directed graph, which is presented in the simplest hierarchical topology by Boolean logic operations (Janes, 1988). The specific process is shown in Fig. 2 (Sakar et al., 2020).

4.2 Results of Logit regression

After determining the variables, an electronic questionnaire was transmitted to students of Guangxi Normal University for filling. In this instrument, KS, X1, X2, X3, X4, and X5 need extra information description, with the remaining elements used to measure the variables based on the importance of the online knowledge sharing intention. Therefore, a 5-point Likert scale was used for the item measurement, with 1, 2, 3, 4, and 5 representing SA, A, N, D, and SD (strongly agree, agree, normal, disagree, and strongly disagree), respectively.

4.2.1 Descriptive statistical analysis

The data were obtained through the website, https://www.wenjuan.com/list/, and the time was observed from October 1 to December 31, 2021. A total of 688 data were obtained from different IDs, with the effective rate of the questionnaire being 90.38% due to the validity of 670 data. In this condition, 80.3% and 19.7% were willing and unwilling to participate (Yes = 1 and No = 0). Both male and female (Age = 1 and Age = 2) also accounted for 48.4% and 51.6% (Mean = 1.52,), with the gender distribution being relatively balanced. Furthermore, the age range was [16–30] (Mean = 22.98), as students were observed not to be very old. Freshman, Sophomore, Junior, Senior, as well as Graduate and above (= 1, 2, 3, 4, and 5) represented 19.7, 14, 13.9, 14.5, and 37.9% (Mean = 3.37), respectively, indicating that the participants were highly dominated by undergraduates. The statistical representation of this result is shown in Table 2.

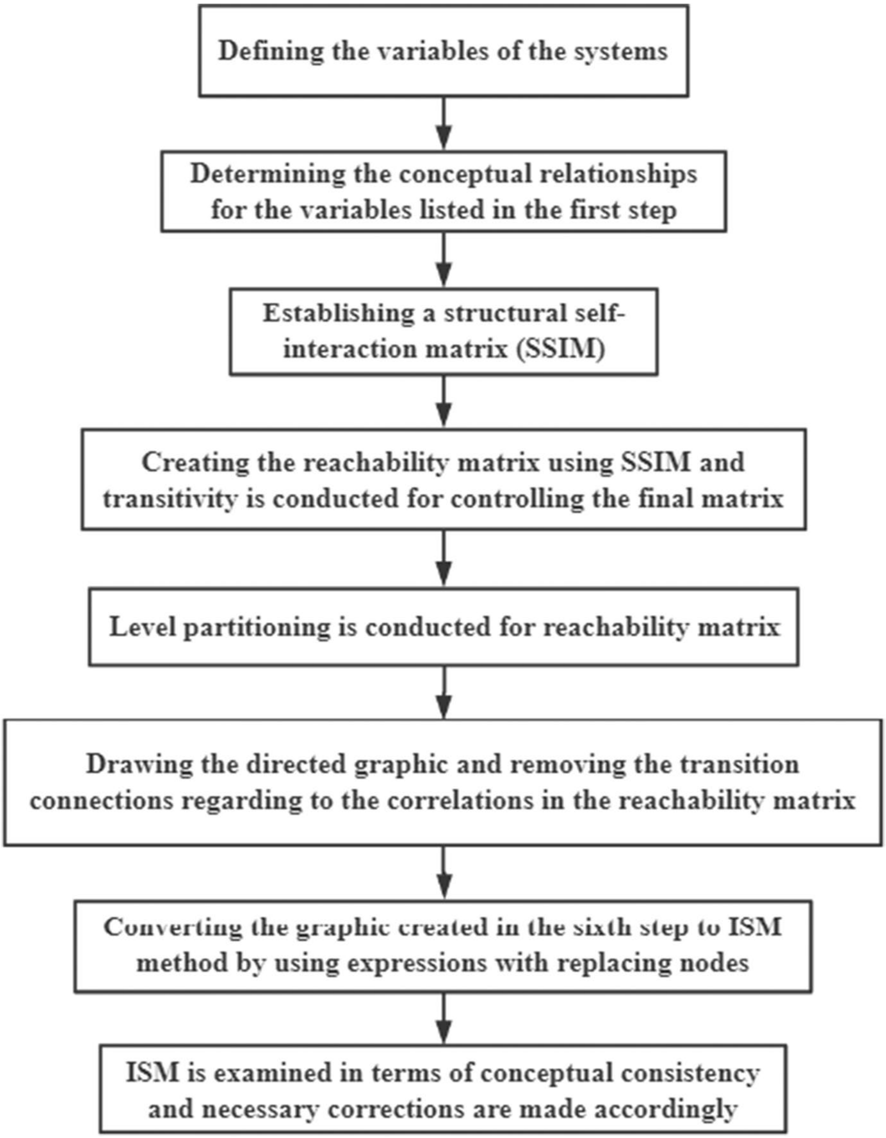


Fig. 2 Stage 1–8 of ISM

4.2.2 Logit regression analysis

To analyze some significant variables, more targeted analyses were carried out using SPSS 22 for Binary Logit regression, leading to the initial test results (Model 1). In this condition, the variables with significant influence (p-value < 0.1) had X4, X5, X8, X10, X14, X16, X17, X18, X20, X23, X24, X25, and X27. This was accompanied by the removal of the remaining insignificant variables, with the 13 initially

Table 2 Statistics date

Variable	Mean ± SD	Variance	Variable	Mean ± SD	Variance
KS	0.8 ± 0.398	0.158	X15	2.46 ± 1.154	1.331
X1	1.52 ± 0.5	0.25	X16	2.06 ± 0.917	0.841
X2	22.98 ± 4.314	18.612	X17	1.78 ± 0.67	0.449
X3	3.37 ± 1.568	2.457	X18	2.74 ± 0.993	0.986
X4	2.41 ± 0.858	0.736	X19	2.49 ± 1.107	1.225
X5	2.04 ± 0.993	0.987	X20	2.32 ± 0.921	0.849
X6	1.61 ± 0.649	0.421	X21	2.22 ± 0.729	0.531
X7	1.48 ± 0.613	0.376	X22	2.14 ± 0.708	0.501
X8	2.83 ± 0.846	0.715	X23	2.28 ± 0.991	0.982
X9	1.43 ± 0.599	0.359	X24	2.91 ± 1.164	1.355
X10	2.54 ± 0.891	0.793	X25	2.78 ± 0.901	0.811
X11	2.4 ± 1.166	1.358	X26	2.74 ± 1.208	1.459
X12	3.23 ± 1.1	1.211	X27	2.32 ± 0.939	0.882
X13	2.12 ± 0.858	0.736	X28	2.7 ± 0.894	0.799
X14	3.899 ± 0.9865	0.973	X29	2.11 ± 1.031	1.063

acquired elements placed into the Binary Logit regression again. Based on the results, all the variables passed the significance test, as shown in Table 3.

From Table 3, the significance probability of the 13 screened variables, X4, X5, X8, X10, X14, X16, X17, X18, X20, X23, X24, X25 and X27, achieved a good level ($R^2 = 0.59$, $Sig = 0.943 > 0.05$). This indicated that the fitting effect of Model 2 was good for subsequent analysis, with Eq. 3 being obtained through the data in Table 3.

$$\begin{gathered} KS = 5.725 - 1.059X4 - 0.538X5 + 0.363X8 + 0.336X10 + 0.341X14 + 0.369X1 \\ +0.699X17 - 0.357X18 + 0.568X20 - 0.409X23 - 0.499X24 - 0.479X25 - 0.585X27 \end{gathered} \tag{3}$$

4.3 ISM results

To facilitate subsequent analysis towards the directed relationship and hierarchy of each variable, the names of the indicators were re-coded as $S1 \rightarrow X4, S2 \rightarrow X7, \ldots, S13 \rightarrow X27$, with their meanings shown in Table 4. The ISM model is constructed according to Sakar (Sakar et al., 2020).

4.3.1 Variable selection and description (Stages 1–2)

In Table 1, the corresponding literature explained the selection of each variable, with the II level definition being subsequently evaluated as the 13 significant variables were obtained through Logit analysis.

Table 3 Logit Model regression results

Variable	Model 1		Model 2	
	B	Sig	B	Sig
X1	-0.066	0.832		
X2	-0.074	0.504		
X3	0.157	0.608		
X4	-1.068	0.00***	-1.059	0.00***
X5	-0.52	0.009***	-0.538	0.004***
X6	-0.231	0.37		
X7	0.485	0.131		
X8	0.432	0.015**	0.363	0.033**
X9	0.098	0.764		
X10	0.344	0.043**	0.336	0.041**
X11	0.088	0.549		
X12	0.104	0.462		
X13	-0.219	0.292		
X14	0.336	0.065*	0.341	0.050*
X15	0.05	0.778		
X16	0.375	0.033**	0.369	0.029**
X17	0.676	0.006***	0.699	0.001***
X18	-0.302	0.084*	-0.357	0.030**
X19	0.171	0.319		
X20	0.589	0.007***	0.568	0.005***
X21	0.023	0.912		
X22	0.023	0.913		
X23	-0.344	0.059*	-0.409	0.015**
X24	-0.529	0.003***	-0.499	0.002***
X25	-0.477	0.009***	-0.479	0.005***
X26	-0.027	0.863		
X27	-0.593	0.005***	-0.585	0.002***
X28	-0.097	0.555		
X29	-0.127	0.478		
Constant	5.912	0.024**	5.725	0.000***
Nagelkerke R^2	0.603		0.59	
Sig	0.681		0.943	

4.3.2 Developing SSIM matrix (Stage 3)

To determine the relationship between the variables, the structural self-interaction matrix (SSIM) was developed in Eq. 4 as follows (Mukeshimana et al., 2021):

Table 4 The variable names of the new encoding and its meanings

Original	New	Meaning
X4	S1	Weekly time on online learning
X5	S2	Daily time spent on social media
X8	S3	Social presence, the degree to which personal are salient in online interactions
X10	S4	Learning more knowledge, that students are interested in
X14	S5	Be encouraged or recognized by others
X16	S6	The relevance of knowledge sharing
X17	S7	Quality of knowledge sharing, the knowledge shared is interrelated and valuable for discussion
X18	S8	The content of knowledge sharing is trustworthy
X20	S9	Reward mechanism, offer substantial rewards to those who contribute to online knowledge sharing
X23	S10	Atmosphere of knowledge sharing, number of participants in discussions and number of knowledge sharing
X24	S11	Access common resources, free knowledge links and public learning resources
X25	S12	Privacy Security, such as sharer's real name, sex, etc
X27	S13	Delete or block information, implify the process of finding information

$$s_{ij} = \begin{cases} V : i \rightarrow j \\ A : j \rightarrow i \\ X : i \leftrightarrow j \\ O : i - j \end{cases} \tag{4}$$

V when Factor i affects Factor j;

A when Factor j affects Factor i;

X when i and j affect each other;

O when i and j are unrelated.

To ensure the objectivity and scientific relationship between the two variables, the context association needs to be determined by the comprehensive perceptions of multiple experts (Attri et al., 2013). In this condition, five educational field experts were consulted, with their evaluations being expressed as a matrix (SSIM), which was obtained after the return visit and revision of ambiguous topics (Table 5).

4.3.3 Transforming SSIM into accessible matrix (RM) (Stage 4)

The SSIM matrix was initially transformed into an adjacency expression, with the transformation rules observed as follows:

Table 5 SSIM

Variable	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
S1		O	O	X	A	O	O	O	O	O	O	O	O
S2			V	O	O	O	O	O	O	O	O	A	O
S3				O	O	O	O	V	O	A	O	O	O
S4					O	A	A	O	O	O	V	O	V
S5						O	X	O	X	O	O	O	O
S6							O	O	O	V	V	O	V
S7								V	O	O	O	O	O
S8									O	O	O	A	O
S9										O	O	O	O
S10											O	A	O
S11												O	V
S12													V
S13													

– When (i, j) entry in SSIM is V, then (i, j) = 1 and (j, i) = 0 in the initial RM
– When (i, j) entry in SSIM is A, then (i, j) = 0 and (j, i) = 1 in the initial RM
– When (i, j) entry in SSIM is X, then both (i, j) and (j, i) = 1 in the initial RM
– When (i, j) entry in SSIM is O, then both (i, j) and (j, i) = 0 in the initial RM.

This was accompanied by the calculation of the reachable matrix (Eq. 5), using the Boolean operation rules of MATLAB R2017a.

$$M = (W + I)^{k+1} = (W + I)^{k} \neq (W + I)^{k-1} \neq \dots \neq (W + I)^{2} \neq (W + I) \tag{5}$$

Table 6 RM

Variable	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
S1	1	0	0	1	0	0	0	0	0	0	1	0	1
S2	0	1	1	0	0	0	0	1	0	0	0	0	0
S3	0	0	1	0	0	0	0	1	0	0	0	0	0
S4	0	0	0	1	0	0	0	0	0	0	1	0	1
S5	1	0	0	1	1	90	1	1	1	0	1	0	1
S6	0	0	1	1	0	1	0	1	0	1	1	0	1
S7	1	0	0	1	1	0	1	1	1	0	1	0	1
S8	0	0	0	0	0	0	0	1	0	0	0	0	0
S9	1	0	0	1	1	0	1	1	1	0	1	0	1
S10	0	0	1	0	0	0	0	1	0	1	0	0	0
S11	0	0	0	0	0	0	0	0	0	0	1	0	1
S12	0	1	1	0	0	0	0	1	0	1	0	1	1
S13	0	0	0	0	0	0	0	0	0	0	0	0	1

M, W, I, k indicate adjacency, reachable, and identity matrixes (13×13), as well as the number of sum operations. The reachable matrix was then obtained after 3 operations, as shown in Table 6.

4.3.4 Level division (Stage 5)

To obtain the reachability $R(S_i)$ and antecedent $A(S_i)$ sets, the reachable matrix was decomposed. This was based on the rules of the hierarchical division, which stated that when $R(S_i) \cap A(S_i) = R(S_i)$, then S_i is the element of the highest level (L1). This led to the location of the row and column in the reachable matrix, with continuous determination observed in the elements of other levels (Table 7).

Based on Table 7, the results were obtained after 8 decompositions, with the 13 elements being divided into 8 levels, i.e., 4, 3, and 1 layer containing 1, 2, and 3 variables.

4.3.5 Development of directed graphs and formation of ISM (Stages 6–7-8)

Using the directed relationship and hierarchical division in Tables 5 and 7, the transitive order and ranking level among the 13 variables were determined, with the final ISM model being created in Fig. 3.

From Fig. 3, the directional relationship between the variables was observed, with the 13 elements subsequently divided into 8 different levels. This showed that a greater variable level led to a higher role within the model. Based on these results, S9 (Reward mechanism) was the deepest variable with the greatest impact on online knowledge sharing. This was accompanied by S5 (Be encouraged or recognized by others), S6 (The relevance of knowledge sharing content and curriculum learning), and S7 (Quality of knowledge sharing). Meanwhile, the most

Table 7 Level partition summary

Variable	Reachability set	Antecedent set	Intersection Set	Level
S1	1,4,11,13	1,5,7,9	1	3
S2	2,3,8	2,12	2	4
S3	3,8	2,3,6,10,12	3,10	3
S4	4,11,12	1,4,5,6,7,9	4	6
S5	1,3,4,5,7,8,9,11,13	5,7,9	5,7,9	7
S6	3,4,6,8,10,11,13	6	6	7
S7	1,3,4,5,7,8,9,11,13	5,7,9	5,7,9	7
S8	3,8,10	2,3,5,6,7,8,9,10,12	3,8,10	1
S9	1,3,4,5,7,8,9,10,11,13	5,7,9	5,7,9	8
S10	3,8,10	6,10,12	10	4
S11	11,13	1,4,5,6,7,9,11	11	2
S12	2,3,8,10,12,13	12	12	5
S13	13	1,4,5,6,7,9,11,12,13	13	1

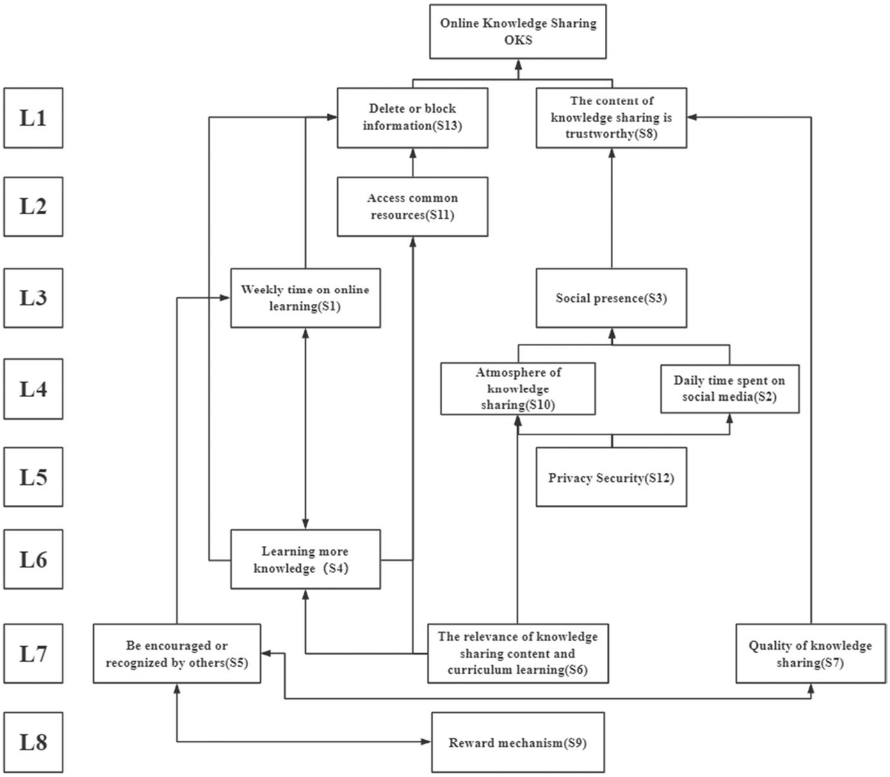


Fig. 3 ISM

shallow variables were S13 (Delete or block information) and S8 (The content of knowledge sharing is trustworthy), which had the least impact on the sharing process.

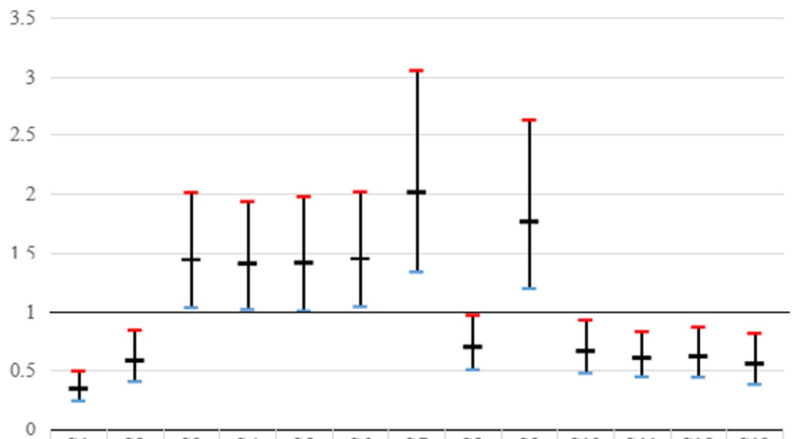
5 Discussion

5.1 Logit results

Based on the results, Logit regression showed that the daily and weekly time spent on social media had negative significant impacts on online knowledge sharing behavior, indicating that longer virtual learning was likely to lead to greater tiredness (Darr et al., 2021). The visual fatigue caused by the frequent use of electronic products was also one of the variables hindering students from participating in online community learning (Kaur et al., 2021). Furthermore, the autonomous virtual environment lacked the support of other participants, causing the inability to effectively deal with learning tasks, which then reduced knowledge sharing behavior (Hsiao et al., 2013). For the remaining individual variables, no significant influence was observed on the sharing process. According to the motivation variables, the following indicators passed the significance test with a positive effect on sharing behavior, namely social presence, being promoted/recognized by others, and more learning knowledge. This proved that the enhancement of social presence promoted students' interaction and collaborative construction, specifically in knowledge sharing, discovery, discussion, and application (Wang & Liu, 2020). In this condition, people also consider the sufficiency of the benefits before participating in online activities (Szymkowiak et al., 2021). Moreover, the encouragement of students' willingness to share had a good effect on social interaction and communication, while interactive enhancement promoted the integration or creation of collective wisdom, sharing, and proficiency exchange (Wang & Lin, 2021). When students are motivated by respect, praise, etc., they are more likely to help others through the dissemination of knowledge (Moghavvemi et al., 2017).

Among the environmental variables, three indicators had a positive impact on online sharing behavior, namely (1) the relevance of knowledge sharing content and curriculum learning, (2) the quality of knowledge sharing, and (3) the reward mechanism. In this case, K-12 online curriculum projects indicated that assignments and high-level intellectual activities contributed to learning outcomes (Zheng et al., 2020). The improvement of the relevance of knowledge sharing activities and course learning was also conducive under the guidance of teachers, to create a good academic atmosphere, as well as allow students to carry out targeted dissemination and opinion discussion. Furthermore, the quality and reward mechanism of knowledge sharing played a great role in promoting these online activities. By judging the quality of the knowledge shared by others, bystanders conveniently selected useful information related to their proficiency. An effective reward mechanism was also a temptation for all online learners, with the acquisition of a regular benefit through sharing behavior being the best of both worlds. However, false information remained a challenge in the virtual environment, due to being often retained as speeches having adverse effects on other participants. To ensure the promotion of students' learning and training, regulation and management also had a positive effect (Gonçalves Costa et al., 2021), although the development trend of knowledge sharing became unpredictable without proper monitoring and guidance. This led to the unguaranteed atmosphere of the sharing process, which often caused a bad psychological effect on participants. Regarding the technical variables, three variables were observed to have negatively significant effects on knowledge sharing, namely common resource accessibility, privacy security, and delete/block information. This proved that learning behavior easily left traces in the virtual environment, with a large amount of data being active on social media. However, personal information was leaked due to the uncertainty of technology management (L. Zhang et al., 2021a, 2021b). In many cases, teachers or technology developers also obtained students' background data for analysis, which often led to uncomfortable conditions, as well as reduction of access and screening behavior in the online environment.

To compare the occurrence ratio of positive or negative variables to online knowledge sharing, their correlation was examined with the representation of a forest map (Fig. 4) (Bitew et al., 2021). Figure 4 shows that the



	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
Odds ratio	0.347	0.584	1.438	1.4	1.406	1.446	2.013	0.699	1.765	0.664	0.607	0.62	0.557
OR Lower CI	0.243	0.406	1.029	1.014	1.001	1.038	1.328	0.506	1.188	0.477	0.446	0.443	0.382
OR Upper CI	0.495	0.84	2.01	1.934	1.975	2.016	3.051	0.966	2.622	0.925	0.827	0.866	0.813

Fig. 4 Forest plot

quality of knowledge sharing had a very great contribution (odds ratio = 2.013, 95%CI = 1.328, 3.051), accompanied by the reward mechanism (odds ratio = 1.765, 95%CI = 1.188, 2.62). Therefore, the great development, as well as the monitoring and management enhancement of knowledge sharing quality is necessary for a virtual environment. To promote others toward participating in these activities, a reasonable reward mechanism also needs to be established. Despite these conditions, weekly online time (odds ratio = 0.347, 95%CI = 0.243, 0.495) still significantly weakened online knowledge sharing. This led to the suggestion of longer weekly learning, to enhance students' perception of virtual dissemination.

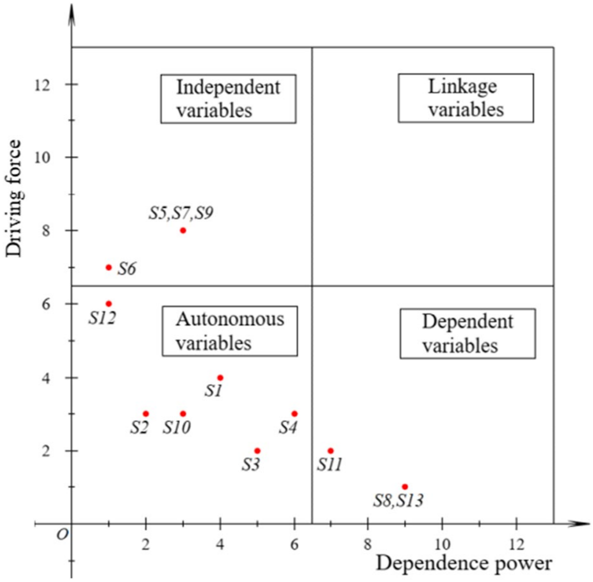
5.2 ISM

Based on the ISM model, 8 hierarchical relationships with different effects were observed among the 13 variables on online knowledge sharing. In this condition, the reward mechanism (S9) was divided into deep variables, due to being the most important contributor to this online process. This was in line with the Logit analysis, where reasonable rewards played a very important role in online knowledge sharing. It also supported several previous studies, where a significant positive relationship was observed between virtual reward and explicit sharing process. Besides this, appropriate reward or effective incentive mechanisms subsequently promoted students' participation in online knowledge sharing (Wang et al., 2021). The content of this sharing process was trustworthy, with the delete

Table 8 Dependence power and driving force

V	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13
DF	4	2	5	6	3	1	3	9	3	3	7	1	9
DP	4	3	2	3	8	7	8	1	8	3	2	6	1

Fig. 5 MICMAC analysis



or block information being divided into superficial variables, due to having the lowest impact on virtual dissemination. This was because few electronic products presently provided all the help of active learning, which led to the effect of students' information screening and comment behavior (Parramore, 2019). It was based on the low trust relationship on social media, as most of these platforms were unable to obtain effective reliance association (Wang et al., 2017).

From the ISM model, multiple variables were observed with strong correlation, such as weekly and daily time spent on social media, as well as being promoted/recognized with trust perception and reward mechanism. This indicated that these variables influenced one another, with the effect of one indicator being appropriately strengthened to affect the other. A relationship of multiple variables was also observed with overstepping direction, such as the quality of knowledge sharing (L7), points to be promoted or recognized (L7), and top trust perception (L1). This proved that some complex relationships were still observed in the hierarchy of the sharing process. To measure the driving force and dependence power of various variables, a subsequent analysis was performed. In this condition, the number of reachability and antecedent sets for each variable represented the Driving force and Dependence power, respectively (Table 8) (Zhao et al., 2019).

According to Table 8, the dependence power and driving force represented the X and Y axes, respectively. The distribution of Autonomous, Dependent, Linkage, and Independent variables was also obtained on the graph of four quadrants (Fig. 5). In this condition, the position of each point represented the category where the corresponding variables belonged. This showed that Autonomous variables had weak driving force and dependence, which generally possessed little correlation with the system. Dependent variables also had weak driving force and strong dependence, generally belonging to the final risk indicators. This indicated that control strategies need to be placed forward as intervention variables. Linkage variables also had strong driving forces and dependencies, as any related behavioral changes affected all the indicators, leading to instability. Meanwhile, Independent variables had a strong driving force and weak dependence. These confirmed that the variables were Independent of others and were the most critical part of the system (Mukeshimana et al., 2021).

Based on Fig. 5, 7 Autonomous variables (S1, S2, S3, S4, S6, S10, and S12) had a weak correlation with other variables and low influence on online knowledge sharing. In this condition, a total of three Dependent variables (S8, S9, and S11) were observed for careful consideration, due to having strong dependence on other indicators. Three Independent variables (S5, S7 and S9) were also observed to be important to other indicators and should be considered the study focus. Meanwhile, the Linkage variables were not observed in this analysis.

6 Conclusion

Online knowledge sharing had great development potential and practical value in the "technology + education" environment. In this study, the Logit-ISM model was introduced to identify and analyze 13 variables and 8 hierarchies, which significantly affected the online sharing process. The forest map and MICMAC analysis were also developed to carry out a comprehensive discussion of the variables, accompanied by the effective consideration of different indicators and hierarchies of knowledge dissemination activities.

Based on these results, several considerations are conducted for the future of online education. Firstly, teachers or specific hosts are required to formulate participation rewards before the development of online knowledge sharing courses and discussion environments. This is to enhance and promote the enthusiasm and self-recognition belief of virtual members towards participation. Secondly, strengthen the time and trust management of online learning. Teachers or curriculum developers also need to provide a reasonable knowledge sharing topic, to prevent the negative effects of visual and mental fatigue in the online process. They also need to attract learners to participate in knowledge sharing discussions, as well as enhance their sense of social presence and trust perception. Thirdly, a two-way pointing effect was observed between the variables, where $S9 \Leftrightarrow S5 \Leftrightarrow S7$ (Fig. 3) indicated that one variable was improved to influence the effect of the other. This was based on the achievement of a two-way circulation and joint promotion. For example, teachers provided appropriate rewards (S9) when expressing encouragement for students to participate in online sharing (S5). This showed that with practical rewards, they perceived the provided participation benefits (S5), which stimulated enthusiasm and improved the quality of knowledge sharing (S7).

Fourthly, multiple variables' hierarchical relationships were observed, indicating that various directional correlations were observed at different levels. This proved that the transformation of one variable was likely to affect the overall structure, confirming that online knowledge sharing activities need to be analyzed from the entire perspective. For example, enhancing the correlation between online knowledge sharing and course learning (S6) promoted the use of educational technology (S11 and S13). It also improved the atmosphere of distribution and obtained more knowledge (S4 and S10). Fifthly, online learners judged knowledge sharing participation by measuring the following (1) reward mechanism, (2) encouragement and recognition degree of others, (3) the correlation between online sharing and course learning, and (4) quality of knowledge dissemination. This was based on the perspective of the deep variables affecting the online process (L8 and L7). Based on the innovation of this report, four different types of influential variables were summarized by combining the theoretical analyses of SET and TAM. This was accompanied by derivation of the significant variables and the hierarchical structure, using the Logit-ISM. However, synergistic effects or other statistical correlations were observed for all the variables, with significant differences subsequently found among the different populations not utilized in this report. This recommends that the correlation analysis between variables should be carried out in subsequent future studies, based on other perspectives.

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Author contribution JC conceived and designed the study. JC, YZ and LTL have drafted the work, substantively revised the draft. All authors read and approved the final manuscript.

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Data availability The datasets used and/or analysis during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare that they have no competing interests.

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