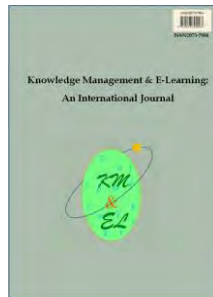

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Partial least square structural equation modelling (PLS-SEM) in knowledge management studies: Knowledge sharing in virtual communities

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Abstract: Partial least square structural equation modelling (PLS-SEM) has been used as a popular research method in various disciplines, including knowledge management (KM). This paper reviews how PLS-SEM has been used in KM studies, which focus on knowledge sharing in the context of virtual community (VC). The review includes 30 articles published from 2007 to 2019. The review discusses the reasons behind the use of the PLS-SEM, data and model characteristics, evaluation of measurement, and structural model in these studies. This paper also provides guidance on how PLS-SEM can be better used and applied in future research.

Keywords: PLS-SEM; Knowledge management; Virtual community; Knowledge sharing

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1. Introduction

Partial least square structural equation modelling (PLS-SEM) has gained the interest of researchers in multiple disciplines, for instance, marketing (Hair et al., 2014a), strategic management (Hair et al., 2012a), tourism and hospitality (Ali et al., 2018; do Valle & Assaker, 2016) and health care (Avkiran, 2018). PLS-SEM has also been termed partial least square path modelling, due to its modelling capability (Henseler et al., 2018). PLS-SEM provides an alternative to covariance-based SEM, which is deemed more flexible in data requirements, specification of relationships, and ability to handle complex models (Sarstedt et al., 2014). The PLS-SEM method uses partial information instead of applying the whole model to explain the indicators co-variations as the CB-SEM does (do Valle & Assaker, 2016). The explained variance of the dependent variables in PLS-SEM is maximized according to the relation of these variables to adjoin construct. The algorithm

is applied to iterate the parameters and are calculated with multiple least squares regressions. Subsequently, the construct scores are created by weighing the sums of items based on a particular construct (Chin, 1998). The word "partial" in its name indicates that the procedure involves an iteration of the parameter separately instead of simultaneously estimating it (Hulland, 1999).

The usage of PLS-SEM has been described as a breakthrough in the path modelling method (Hair et al., 2012a). The PLS-SEM method has been adopted in various fields due to its contribution to facilitating structural equation-based studies. The need to assess the use of PLS-SEM in respective fields reflects the state-of-art application of this method. Across different fields, an in-depth understanding of how these social science scholars adapted the application of PLS-SEM to a particular field can be determined (Ali et al., 2018). In comparison, the application of PLS-SEM in the marketing field is considered matured and fully developed (Hair et al., 2012b), whereas it is still considered relatively new in the tourism and hospitality field (Ali et al., 2018). In other fields, where PLS-SEM is more recent, such as health care, authors often fall short in testing the advanced analysis, which would explain the lack of robustness of the result (Avkiran, 2018). In the KM field, VC is given special attention as the PLS-SEM reporting method requires proper characterization of steps in terms of analysis of measurement and structural model and the reporting of advanced methods. (Ghasemy et al., 2020).

The knowledge management (KM) field has reached maturation in the last two decades (Fauzi et al., 2018). Today's organizations require a proper KM, particularly within the development of the digital economy (Fauzi, 2019). VC or online communities are groups of people who have the same interest, practices, and goals that share knowledge entirely for the benefit of its members (Ye et al., 2015). There are several terminologies used in reference to VC, including the community of practice (COP) (Tseng & Kuo, 2014), professional virtual communities (Tamjidyamcholo et al., 2014), and virtual learning community (Lu et al., 2013). Regardless of the terms, VC is a platform for members to share their knowledge and expertise for others to benefit reciprocally. The flow of information and expertise within the VC would facilitate members to retrieve and at the same time disseminate through virtual discussions and interactive communications.

The motivation and rationale of this review are to broaden the application of PLS-SEM in the KM field, particularly knowledge sharing, as it is the most crucial element (Chang et al., 2015). Moreover, VC has provided its members and users with a knowledge-sharing platform as a vital e-learning medium for knowledge seekers (Pham & Tran, 2020). To date, there has been only one study reviewing PLS-SEM in the KM field (see Cepeda-Carrion et al., 2019). However, Cepeda-Carrion's study is limited in terms of a comprehensive review on the reporting methodology of PLS-SEM and proper presentation of the broad KM discipline. This review, however, delineates an exclusive reporting of PLS-SEM focusing only on VC in KM as one of the preferred segments in this field. Moreover, as studies in VC are expected to expand, researchers would need a guideline that can be referred to when conducting required studies.

This study would benefit future researchers that are interested in a step-by-step updated reporting procedure of the PLS-SEM. It is imperative that the current reporting procedure of the PLS-SEM is standardized with other disciplines within the KM community. In response, this study calls for a holistic review of the PLS-SEM application within the KM discipline. As the digital economy is now being drastically expanded, it is expected that more people will depend on VC for the sharing of and acquiring of

knowledge. Hence, an updated guideline of the PLS-SEM assessment in KM discipline is necessary, especially because there is an escalation in interest among researchers to understand knowledge sharing among members in the organization, particularly in VC (Fauzi et al., 2019; Turyahikayo, 2021).

2. PLS-SEM vs. CB-SEM

In structural equation modelling, two primary approaches have been applied to date. The first SEM has emerged as covariance-based SEM (CB-SEM) (Jöreskog, 1973, 1978). CB-SEM has strict requirements and assumptions for data validity (do Valle & Assaker, 2016). The CB-SEM is used when a hypothesized model has one or more common factors (Henseler, 2017). It estimates the model parameters by allaying to the empirical variance-covariance matrix. It must meet data normality, sample size, reflective construct (i.e., the direction of indicators arrows pointing towards construct), and influential theory in testing a model. However, the latter SEM, PLS-SEM, is known to be variance-based SEM is explicitly more accessible in the sense that it does not have to meet all the strict criteria of CB-SEM. It plays an essential role in solving causality problems within the context of latent variables when assumptions are not met in CB-SEM.

In KM, scholars have favoured PLS-SEM usage over CB-SEM (Chang et al., 2016; Feng & Ye, 2016). Studies in the KM field mostly use composite variables, measure theoretical concepts with multiple items, and apply an interval scale as a strong reason to use PLS-SEM (Cepeda-Carrion et al., 2019). In contrast, KM researchers should apply CB-SEM if common factors variables are specified in their studies. Similarly, VC is considered to be an important sub-field in the broader KM. Hence, analyzing the usage of PLS-SEM in VC is crucial in order to facilitate the future influx of studies in VC that are meant to adapt PLS-SEM.

2.1. Philosophical ground

There are two main philosophical reasons authors must consider before opting for either PLS-SEM or CB-SEM. The first is the measurement philosophy, and the second is the aim of the analysis (Hair et al., 2018). The measurement philosophy is based on the philosophy of either factor or composite based. PLS-SEM would be the preferred option if the author were to choose composites as proxies of latent variables (Rigdon et al., 2017; Hair et al., 2017c). The second reason refers to the aim of the analysis as to either opting for minimizing the difference between the estimated and sample covariance matrices or maximizing the explained variance in endogenous construct (Sarstedt et al., 2017). A distinct difference between PLS-SEM and CB-SEM is that the PLS working principle is to minimize the error terms and to optimize the explained variance of the endogenous variable (Astrachan et al., 2014).

In general, studies incorporating a common factor model should opt for CB-SEM, while studies with composite should prefer PLS-SEM. On the other hand, if a study consists of both factors and composites, a newly adapted method of using the consistent PLS consistent should be applied (Dijkstra & Henseler, 2015). Ultimately, PLS-SEM is the option for predicting analysis rather than to confirm which is preferable in CB-SEM (Hair et al., 2018). The scholarly publication has shown that PLS-SEM is robust and has surged the interest in applied science by granting hypothesized relationships to be tested, so that model estimation is under prediction focus (Sarstedt et al., 2019). PLS-SEM deals with social science construct that applies latent variables. Latent variables in practical are

operated by a common factor in a statistical model. Composite can model the artefacts within the variables (Henseler et al., 2018). Hence, it is a favoured method due to its capability of estimating models containing composites and factors.

2.2. Technical ground

Embedded in the vast literature of PLS-SEM, authors dictate their reasons for choosing PLS-SEM over CB-SEM are based on technical considerations such as the type of study, which generally are confirmatory, exploratory, explanatory, or predictive study. Reasons for data selection technique and data analysis include data normality, number of latent variables, and small sample size (Avkiran, 2018). There are other technical grounds such as having moderated and mediating variables, and the complexity of the model.

2.2.1. Type of research

In general, quantitative research is divided into four primary types, confirmatory, explanatory, exploratory, and predictive. Confirmatory research needs global goodness of fit test due to the difference in the variance-covariance matrix of the model and empirical data (Hair et al., 2017a). Confirmatory and explanatory studies can be classified as causal research as it is usually conducted to test the causal relationship between variables (Henseler, 2018). The difference between these two is that explanatory research seeks to interpret the variation in each context, while confirmatory is conducted to test the underlying theories presented. The main contrast between the two is that explanatory focuses on the specific phenomenon being treated as a dependent variable. Hence, the structural model for this type of study consists of many exogenous variables with only a single endogenous variable. Descriptive research is applied to provide an aggregate level report for construct values. Predictive research is presented, providing forecasting for individual cases. The exploratory research's aim is to identify the relationship among constructs in which new theories can be developed. It aims to identify potential relationships between variables in the model (Cepeda-Carrion et al., 2019). Fundamentally, exploratory is a form of inductive reasoning where PLS-SEM provides the connection between path model (theory) and data.

Usually, confusion occurs when selecting between PLS-SEM or CB-SEM for exploratory and confirmatory research. It has been clearly stated by Hair et al. (2017b) how exploratory differs from confirmatory research. Exploratory research is conducted when there are undefined or unclear problems or when there is a lack of information to make a conceptual distinction or connect the relationship between variables in question. Exploratory research can be applied to derive hypotheses from qualitative results, but it requires a quantitative method to test the hypotheses. On the other hand, confirmatory research is applied to test the well-documented causal theories and test the specified hypotheses (Hair et al., 2017b).

2.2.2. Small sample size

PLS-SEM maintains its fundamental function in the context of a small sample size as the basis of its methodology of not estimating overall model parameters simultaneously (Rigdon et al., 2017). As the name suggests, it works by estimating the structural model partially, equation one by one. Hence, the requirement for minimum sample size in producing model estimates lean on the model ramification of a particular equation, which is much lesser than the overall model complexity. It has been suggested that compared to

its predecessor CB-SEM, PLS comply and executes better in the event of a small sample size. The reason is that CB-SEM tends to develop non-convergence problems and unsuitable solutions (Henseler et al., 2014).

However, recent arguments stated that claiming PLS is more efficient with small sample size is misleading because it neglects the goal of achieving sufficient statistical power (Kaufmann & Gaeckler, 2015). The sample size is a crucial issue in structural equation modelling as it directly influences the model fit, parameter estimates, and statistical power (Peng & Lai, 2012; Kaufmann & Gaeckler, 2015). Goodhue et al. (2012) suggested that sample size requirements in PLS-SEM are more significant than assumed. In this regard, a small sample size is particularly true for models consisting of large effect sizes and strong paths. At the same time, it is not applicable for models that have small effect sizes and produce modest and weak path coefficients (Kock & Hadaya, 2016). Hence, researchers applying PLS must have a large enough sample size to achieve adequate statistical power (Riedl et al., 2014).

2.2.3. Non-normal sample size

PLS is mainly sufficient for analyzing non-normal data due to its bootstrapping procedure that places minimal restrictions on sample distributions by resampling techniques (Chin et al., 2003). As studies in knowledge sharing depend on human behaviour, Goodhue et al. (2012) stated that behavioral studies are commonly not normal. PLS has an advantage due to its ability to handle non-normal data. In terms of the ability to manipulate data, PLS-SEM is relatively robust when dealing with skewed data than CB-SEM (Hair et al., 2014b). PLS's strength is that it provides preliminary theory-building while CB-SEM outweighs PLS in terms of model validation (Lowry & Gaskin 2014). That being said, in the case of a well-developed theory used with effective data measurement, CB-SEM is the most appropriate. The problem in social science research is that data normality is almost impossible (Hair et al., 2017c). CB-SEM can fundamentally handle non-normal data, but it requires a large sample size (Hair et al., 2017c). The non-normality of data can be shown through several properties such as skewness and kurtosis. The Monte Carlo simulations testing the PLS-SEM algorithm showed that the PLS-SEM is robust enough to deal with a non-normal dataset when other algorithms might not have (Kock, 2016).

2.2.4. Formative construct

It was reported that many authors do not understand or know how to report formative measurement models (Hair et al., 2017b). The underlying concept of a reflective and formative construct is in the direction of causality. In the reflective construct, causality refers to how the construct is related to the indicators, while in formative, the construct is the causal manifestation of the indicators (Aguirre-Urreta & Marakas, 2014). A formative construct has a reversed causality direction. Phang et al. (2009) stated that the PLS method was selected due to the formative construct that is used in the model. The construct of usability and sociability is more appropriate to be modelled with PLS-SEM rather than CB-SEM. According to Aguirre-Urreta and Marakas (2014), most of the studies (16 out of 19) that apply a formative construct have either an exogenous or endogenous variable. This is contributed by PLS-SEM's ability to work with complex identification, mainly when dealing with an endogenous construct. This issue is a problem that involves a tedious process when using CB-SEM.

3. A review of KM studies using PLS-SEM

This section presents a review of 30 studies on KM using PLS-SEM. As shown in Table 1, these studies are from various top-tier journals, mainly from within the knowledge management field.

Table 1
30 studies included in the review

No	Authors	Journal	Tools	Reason for PLS	Sample size
1.	Ma & Agarwal (2007)	Information Systems Research	PLS Graph	Non-normal data	666
2.	Staples & Webster (2008)	Information Systems Journal	Not stated	Mediator	824
3.	Zboralski (2009)	Journal of Knowledge Management	PLS-Graph	Formative constructs	222
4.	Phang et al. (2009)	Journal of the Association for Information Systems	Not stated	Formative construct	115
5.	Zhang et al. (2010)	International Journal of Information Management	SmartPLS	Small sample size	144
6.	Chai & Kim (2010)	International Journal of Information Management	Not stated	1. Exploratory 2. Non-normal data	485
7.	Fang and Chiu (2010)	Computers in Human Behavior	PLSGraph	1. small sample 2. Non-normal data	142
8.	Jeon et al. (2011a)	Expert Systems with Applications	PLS-Graph	Formative construct	179
9.	Jeon et al. (2011b)	Journal of Knowledge Management	Not stated	Theory development	282
10.	Kim et al. (2011)	Computers in Human Behavior	Not stated	Not stated	185
11.	Ku (2014)	International Journal of Tourism Research	PLS-Graph	Not stated	235
12.	Yoon & Rolland (2012)	Behaviour & Information Technology	PLS-Graph	Theory development	209
13.	Xu et al. (2012)	International Journal of Human-Computer Interaction	PLS-Graph	Not stated	399
14.	Yan et al. (2013)	Computers in Human Behavior	SmartPLS	Theory development	232
15.	Chen et al. (2013)	Internet Research	VisualPLS	Moderator analysis	219
16.	Liao et al. (2013)	Online Information Review	Not stated	Complex model	473
17.	Lin & Huang (2013)	Internet Research	VisualPLS	Sample size	167
18.	Hau et al. (2013)	International Journal of Information Management	PLS-Graph	Non-normal data	2010

19.	Tseng & Kuo (2014)	Computers & Education	Not stated	Theory development	321
20.	Lai & Chen (2014)	Computers in Human Behavior	SmartPLS	Small sample	324
21.	Tamjidyamcholo et al. (2014)	Computers & security	SmartPLS	1. Small sample 2. Formative construct	142
22.	Chang et al. (2015)	Information Systems Management	Not stated	1. sample size, and 2. residual distribution	150
23.	Gang & Ravichandran (2015)	IEEE Transactions on Engineering Management	SmartPLS	1. Small sample 2. Complex model	118
24.	Ye et al. (2015)	Electronic Commerce Research and Applications	SmartPLS	1. Complex model 2. Sample size	169
25.	Yuan et al. (2016)	Computers in Human Behavior	SmartPLS	Non-normal data	364
26.	Feng & Ye (2016)	Computers in Human Behavior	SmartPLS	1. Exploratory 2. Multi-stage model	169
27.	Yen (2016)	Behaviour & Information Technology	SmartPLS	Not stated	201
28.	Chang et al. (2016)	Online Information Review	SmartPLS	1. Exploratory 2. Formative construct	253
29.	Hau & Kang (2016)	International Journal of Information Management	PLS Graph	1. Formative construct 2. Mediating effect 3. Non-normal data	140
30.	Alsharo et al. (2017)	Information & Management	Not stated	Not stated	193

3.1. Reason for choosing PLS-SEM

Within the 30 studies reviewed, authors have stated several reasons for choosing PLS-SEM in their analysis. The most common reason stated by eight different studies (26.7%) is the use of a small sample size (26.7%). The second most common reason for using PLS-SEM is theory development (7 studies, 23.3%). Non-normal data and the use of formative construct each with six studies (20%). Other reasons that authors opted for PLS-SEM are model complexity (3 studies, 10%), the use of mediator analysis (2 studies, 6.67%), and moderator analysis (1 study, 3.33%). Five studies did not mention the reason for using PLS-SEM. Table 2 summarizes the reasons for using the PLS-SEM for studies on knowledge sharing in VC.

3.2. Result reporting

This review outlines the 30 studies beginning with descriptive statistics. It consists of all the necessary reporting of the sample size collected, the number of latent variables, and indicators. Apart from that, the number of structural paths connecting exogenous and endogenous variables are also reported. This study also presents the mode of measurement, either being reflective only model, formative only, or a combination of both reflective and formative.

Table 2
Reasons for using PLS-SEM

Reason for using PLS-SEM	Frequency (n = 30)	Percentage
Sample size	8	26.7
Non-normal data	6	20
Theory development	7	23.3
Formative construct	6	20
Model complexity	3	10
Mediator analysis	2	6.67
Moderator analysis	1	3.33
Not mentioned	5	16.7

In the specific PLS analysis, PLS models are analyzed by two steps: the measurement model (or known as the outer model) and structural model (or known as the inner model) (Henseler et al., 2015). The measurement model assesses the relationship between a construct and its observed items, while the structural model assesses the relationship between the constructs. Measurement model assessment consists of the analysis of indicator loading, construct reliability, convergent validity, and discriminant validity. As for the structural model, the assessment includes the coefficient of determination, effect size, predictive relevance, the significant level of p-value, and the t-value. The bootstrapping re-sampling technique applying numbers of iteration is also included in the structural model.

3.3. Descriptive statistics

Table 3 shows the overall descriptive statistic of the studies in this review. The average sample size included in all the studies is 325 samples with a median of 219. The study with the lowest number of respondents had only 115 (Phang et al., 2009), and the largest was 2010 respondents (Hau et al., 2013). None of the studies used less than 100 sample sizes, whereas six studies used less than 150 samples (20%). This review shows that authors justify their reason for choosing PLS-SEM based on a small sample size with seven studies. This is supported by six studies that have less than 150 respondents. Authors with a small sample size might have chosen PLS-SEM due to their limited sample size despite current findings and strong caution from several gurus in opting for PLS-SEM over CB-SEM for a small sample size. (Hair et al., 2017a; Henseler et al., 2015).

The average latent variables included in all the studies were 7.43, with a median of 7.50. This number is slightly similar to other studies such as Kaufmann and Gaeckler (2015) (Mean 7.05, Median 6.05), do Valle and Assaker (2016) (mean 6.02, median 6.0)

and Hair et al. (2012b) (Mean 7.94, median 7.00). The range of the variables are from 4 to 11, which illustrates the extent of the complexity of models in this field. This shows that most of the model in this study within the review is simple to moderate. This is supported by the number of structural paths ranging from 4 to 15 (mean 8.30 and median 8), which can be considered few to moderate.

Table 3
Descriptive statistics of sample and model characteristics

Criterion		Frequency (n = 30)
Sample size	Mean	325
	Median	219
	Range	115-2010
	Less than 100 sample	0
	Less than 150 sample	6
Latent variable	Mean	7.43
	Median	7.50
	Range	4-11
Indicators	Mean	27.13
	Median	25
	Range	11-49
	Single indicator	0
Structural path	Mean	8.30
	Median	8.00
	Range	4-15
Mode of measurement	Only reflective	23
	Only formative	0
	Reflective and formative	7

The indicators in the studies show that they range from 11 to 49, with a mean of 27.13 and a median of 25. This review revealed that none of the studies applied a single item construct in the model. PLS-SEM requires a sufficient number of indicators based on the construct to achieve an adequate outer model quality (Hair et al., 2012b). Hence, the use of a single item can only be considered if only 1) unavoidable small sample size, 2) expectation of effect size of 0.30 and lower, and 3) items of the original multi-item scale are homogeneously high (for example, Cronbach's alpha more than 0.90) and 4) items are semantically repetitious (Diamantopoulos et al., 2012). These are the conditions for a single item to be considered an endogenous variable that focuses on the explained variance by prioritizing the prediction (Hair et al., 2012b).

3.4. Measurement model

The first step of applying PLS-SEM is to assess the measurement model. Reflective measurement model involves reliability (indicator loading and internal consistency reliability) and validity (convergent and discriminant). For the indicator loadings, the value should be more than 0.70 to ensure indicator reliability (Hair et al., 2014a). Items below 0.70 should be deleted as it would bring adverse impact on construct measures of

reliability in the form of internal consistency and convergent validity (Sarstedt et al., 2014).

Reliability and validity of items within the construct are the primary concern in the measurement model. The assessment depends on several conditions, mainly whether a construct is categorized as reflective or formative. A distinct evaluation of the measurement model is on the matter of reflective and formative construct. A specified test is needed to differentiate the distinct difference between reflective and formative construct (Hair et al., 2017b).

3.5. Reflective measurement model evaluation

A reflective measurement assesses the reliability of the item (indicator reliability and internal consistency, reliability, and validity (convergent and discriminant validity). The threshold value for indicator loading should pass the 0.7 value to ensure that it is reliable. The threshold value in a confirmatory study should at least meet 0.7 and 0.6 in the exploratory study (Henseler et al., 2015). Reflective indicators are items that can be possibly omitted that belong to a construct (Hair et al., 2014a). These items can be omitted without changing the conceptual meaning of a construct. It is also highly correlated and interchangeable. As for internal consistency analysis, it is assessed by Cronbach's alpha and composite reliability (Hair et al., 2014a). In the case of a formative construct, a significant contrast is that internal consistency reliability is not needed. It must include an additional reflective measured variable, the construct nomological net, for the convergent validity to be calculated (Hair et al., 2017a).

3.6. Indicator loading and construct reliability

As shown in Table 4, 27 studies reported the indicator loading (90%). As for the construct reliability, 29 studies reported composite reliability (96.67%), while 23 studies reported Cronbach's alpha (76.67%). Cronbach alpha, despite being used extensively in organizational research; scholars has begun shifting to other reliability coefficients due to its poor scores (Cho & Kim, 2015). Composite reliability is one of them. All the studies reported AVE.

The first step in evaluating the reflective outer models is to establish both the construct reliability and validity (Hair et al., 2014b). A more well-known measurement of internal consistency reliability is using composite reliability. Previously, many researchers have long been using Cronbach Alpha. It is more justifiable to apply composite reliability due to its assumption on the indicator loading of not being equal in tandem with the PLS-SEM algorithm of not having an indicator in favour based on the model estimation of individual reliabilities. Secondly, Cronbach alpha is unstable due to the number of items that underestimates the construct reliability. In evaluating the reliability, a higher value implies that the reliability is high. Value of 0.60 to 0.70 is acceptable for exploratory research, while 0.70 to 0.95 is regarded as "satisfactory to good" (Sarstedt et al., 2014).

According to McNeish (2018), Cronbach's alpha is no longer relevant due to its strict estimate based on its three assumptions 1) Adherence to tau equivalence 2) Scale items on continuous and normally distributed 3) Errors of items do not covary and 4) The scale is unidimensional. However, Raykov and Marcoulides (2019) state that researchers should not abandon Cronbach alpha based on its point and interval estimates. As far as this study is concerned, even though Cronbach alpha is used less than composite

reliability, it provides a lower-level estimation of internal consistency analysis that is very useful for complimenting composite reliability. Hence it is still encouraged to report Cronbach's alpha in social science studies to compare the value with composite reliability.

Composite reliability circumvents the underestimation that is usually computed by Cronbach's alpha and entertains the indicator reliabilities performed by PLS-SEM (Avkiran, 2018). Composite reliability should be more than 0.70 in confirmatory studies and at least 0.60 in exploratory studies (Hair et al., 2012a). Value exceeding 0.95 is an indicator of redundancy (Hair et al., 2014b).

3.7. Convergent validity

For validity, convergent and discriminant analysis must be validated. The measurement of convergent validity is the average variance extracted (AVE) assessment, which should meet at least 0.5. The average variance extracted (AVE) is an indicator of variable convergence to evaluate the items of either being converged to its desirable construct or variable. It is the extent to which an individual item strongly agrees, which is known as converging among them in representing the construct they were employed to measure. AVE was reported in all of the studies (100 percent). It is evaluated by examining the indicator's outer loading to dictate construct AVE (Hair et al., 2017a). To achieve 50% of the AVE, the outer loadings should be more than 0.708, due to the AVE calculation (square root of the mean loading value), which would result in the 50% variance (Henseler et al., 2016). An adequate convergence illustrates that more than half of the variance in construct indicators is included in the score.

3.8. Discriminant validity

For discriminant validity, there are three assessment criteria which include the Fornell-Larcker Criterion and cross-loading, which are the traditional assessment criteria (Fornell & Larcker, 1981). An advanced and more accepted assessment today is by the Heterotrait-Monotrait ratio of correlation (HTMT) criterion (Henseler et al., 2015). Both cross-loadings and the Fornell-Larcker criterion overstate the discriminant validity problem (Hair et al., 2017b). Our findings show that 28 studies (93.3 percent) still apply the Fornell-Larcker criterion and nine studies (30 percent) reported cross-loading. Despite a recent discriminant validity assessment, HTMT was not reported in any of the studies. This is due to the reason that HTMT analysis had only emerged in the PLS-SEM community in the year 2015 (Henseler et al., 2015), while studies in KM especially in VC, are scarce and limited.

3.9. Formative measurement model evaluation

In terms of model measurement, 23 studies have only reflective indicators, while no studies have only formative. Seven of them have both reflective and formative indicators. Despite that, analysis required in the formative model was not performed by the authors, except indicator contribution to the construct of p and t values. Indicator weights, by far the most essential analysis in the formative model was not reported. As VC is regarded as a new avenue in KM studies, having extensive formative analysis would create a distinct issue in contemplating the complex model. It was cautioned that the interpretation of the PLS-SEM result on the item level should be carefully made as to the potential emergence of biases based on indicator weight on the issue of prioritization (Rigdon et al., 2017). In formative measurement, statistical significance and multicollinearity are important. This

is due to insignificant outer loadings or weights; the indicator's relevance would not be supported in providing content to the formative index (do Valle & Assaker, 2016). As for multicollinearity within a set of indicators to a particular formative construct, it is essential because it can create a lack of statistical significance for formative indicator weight estimate (Grewal et al., 2004).

Other empirical test required in the formative measurement model is to state the significance of weights using standard errors significance level using t-values or p-values for indicator weights. Authors must also report the multicollinearity using VIF or tolerance (Hair et al., 2017b). Future studies in KM, in general, should expect further extensive analysis in formative measurement. As noted by Hair et al. (2017a), a recent contemporary method of formative model assessment should be followed, especially for the redundancy analysis, an indicator of multicollinearity and indicator's relative and absolute contribution to the construct (Ali et al., 2018).

Table 4
Measurement model evaluation

Criterion		Frequency (n = 30)	Percentage
Reflective measurement models			
Indicator reliability	Indicator loadings	27	90
Construct reliability	Composite reliability	29	97
	Cronbach's alpha	23	77
Convergent validity	Average variance extracted	30	100
Discriminant validity	Fornell-Larcker criterion	28	93
	Cross loadings	9	30
	HTMT criterion	0	0
Mode of measurement	Only reflective	23	77
	Both	7	
Formative measurement models			
Indicators contribution to the construct	Indicator weights	0	0
	P or t values	3	
	Redundancy analysis	0	0
	VIF	0	0
	Tolerance	0	0

3.10. *Structural model*

The second stage of SEM analysis is to test the relationship between the constructs. It is also referred to as a causal relationship to denote the theoretical structure between the construct of either being meaningful and/or significant (Hair et al., 2017b). In brief, this second stage assesses the structural study theory by measuring the structural model relationship according to previous empirical research of which the hypotheses are statistically tested.

3.11. Coefficient of determination R^2

For explained variance, analyzed by the coefficient of determination R^2 , almost all the studies reported except for one (96.7%). The value of R^2 relies upon its underlying rule of thumb, with 0.67, 0.33, and 0.19 representing the strong, moderate, and weak levels of the endogenous construct (Chin, 1998). Relatively, a cut-off value of 0.10 was employed to determine whether an endogenous construct could be marginally accepted, explained by a set of the exogenous construct (Falk & Miller, 1992). Being the fundamental analysis of every structural measurement, it is no surprise that R^2 is reported in all the studies. Table 5 illustrates the findings of the structural model in this review.

Table 5
Structural model evaluation

Criterion		Frequency (n = 30)	Percentage
Explained variance	Coefficient of determination R^2	29	96.67
	Effect size f^2	1	3.33
	Predictive relevance Q^2	1	3.33
Path coefficient estimates	Beta	29	96.67
	P-values	12	40.0
	t-values	7	23.3
	P-values & t-values	11	36.7
	Bootstrapping		
	500	5	16.7
	1000	1	3.33
	2000	1	3.33
	5000	2	6.67
	Stated	4	13.3
Not stated	15	50.0	

3.12. Effect size f^2

The effect size is essential to detect weak relationships (Nitzl, 2016). Only one study reported the effect size (Zhang et al., 2010). It is somewhat surprising that studies in the knowledge management field lack in terms of effect size reporting. The effect size is a statistical procedure that measures the importance of an exogenous construct(s) on any endogenous construct by recalculating R^2 . The exogenous construct is omitted one at a time in producing the recalculation of the R^2 (Avkiran, 2018). As mentioned by Cohen, the effect size value is 0.02 for small, 0.15 for moderate, and 0.35 for large effect. Studies are required to report effect size in support of the statistical significance (P -value and t -value). The extent of effect size is to avoid a Type II error where one can probably report no effect when it actually exists (Sullivan & Feinn, 2012).

3.13. *Predictive relevance Q^2*

The Stone-Geisser index is an assessment of out-of-sample prediction (Rigdon, 2012). Only one study, Yuan et al. (2016), reported predictive relevance (3.33 percent). The predictive relevance Q^2 and relative predictive relevance q^2 provide the option to assess the model's practical relevance (Hair et al., 2017a; Richter et al. 2016). It depends on the blindfolding procedure, which deletes some data points in a systematic and technical procedure and uses the remaining data for estimating the path model. The difference between the omitted values and predicted data serves as the model's predictive relevance. The value of Q^2 should be more than 0 ($Q^2 > 0$) to indicate predictive relevance. q^2 for endogenous latent constructs with reflective models having 0.02, 0.15, 0.35 for weak, moderate, and strong degrees of predictive relevance (Chin, 1998). In some studies, the author has referred to R^2 values (not Q^2 values) as the basis to evaluate predictive relevance level Navarro et al. (2010).

3.14. *Path coefficient estimate*

The modelling part of PLS-SEM is not as efficient as the maximum likelihood of the covariance-based SEM (Henseler et al., 2015). PLS-SEM fared higher than CB-SEM in the loadings and path coefficients (Hair et al., 2017b). PLS-SEM contributes a large different parameter estimate as it is based on total variance, while CB-SEM is based on common variance. All the studies reported the path coefficient values (Beta -value) with 29 studies (96.7 percent). Several studies did not report on the path coefficients' significance by reporting p or t -values. Only 19 of the studies reported either P -values or t -values. Eleven of the studies reported both values (36.7 percent). Due to the nature of PLS-SEM, which does not predict a particular data distribution, employing a significance test is required to derive standard error parameters using resampling method, i.e., bootstrapping (Ali et al., 2018).

As for the bootstrapping procedure, only half of the studies reported (50 percent). Only half (50 percent) of the studies reported the bootstrapping method. Most of the reported bootstrapping values used the 500 iterations (5 studies, 16.7 percent), 1000 and 2000 iteration with 1 study each, and 5000 with two studies (6.67 percent). However, this number is considerably low compared to the suggested bootstrapping of 10,000 (Streukens & Leroi-Werelds, 2016). The bootstrapping procedure works by having a large number of subsamples taken from the original sample and replacing it to produce a standard bootstrap error (Wong, 2013). This standard error would produce a significance test for both the inner and outer model (T -values) by approximating the data normality. The higher the bootstrapping iteration would create a better approximation of the standard error and significance of the T statistics.

3.15. *Advanced analyses using PLS-SEM*

The advancement in using PLS-SEM in social science has made the data assessment and model relationship a more complicated analysis. This review shows that only a handful of studies applied advanced analyses of PLS-SEM. Only ten studies (38 percent) ran moderation analysis, while only two (23 percent) ran moderating analyses. This review discovered that no studies had been found to apply other advanced analysis features that are readily available in PLS-SEM features, such as unobserved heterogeneity and endogeneity (Ali et al., 2018). Researchers are used to the basic application of PLS-SEM and tend to ignore or are unable to use a more advanced analysis such as CTA-PLS, FIMIX-PLS, multigroup analyses, and moderator (Ringle & Sarstedt, 2016). KM studies

in this context should use and exploit these advanced techniques to further reiterate and substantiate findings in a holistic executable manner.

4. Discussion

Studies in KM are rapidly evolving as much as the development of VC. VC has provided an efficient and effective platform for members to participate in knowledge-sharing activities. This review paper corroborates 30 studies using the VC platform where members share knowledge and analyze the methodology of applying PLS-SEM. The application of PLS-SEM within this discipline is intriguing, as VC is an emerging yet undiluted discipline for scholars in KM.

Contributing to PLS-SEM's robustness, the growth in VCs' study will be expected to increase in the coming years. In this instance, as PLS-SEM is promoted in virtual KM studies, adherence to crucial guidelines and suggested practices should be followed. Firstly, it is encouraging to choose an appropriate measurement model, particularly in the presence of formative measurements. Researchers would have to make a thorough understanding of the theoretical construct to execute an accurate data analysis. Another aspect is the validity between explanatory and exploratory research regarding its inner model's quality of effect sizes. The effect size would be necessary for exploratory research for building theory based on empirical data (Richter et al., 2016). In the structural model analysis, Sarstedt et al. (2019) have pointed out that PLS-SEM has received the development in assessing the robustness of the structural model results. Robustness issues include nonlinear effects, endogeneity, and unobserved heterogeneity.

5. PLS-SEM software

The first-ever PLS-SEM software was LVPLS (Lohmoller, 1988). This development of this software was instead stalled because the software had no graphical user interface and the death of the program author (Henseler, 2017). However, in 2003, a more advanced PLS-Graph software with embedded graphical user interface for PLS-SEM analyses was developed (Chin et al., 2003). The breakthrough came in 2005 when the application of PLS-SEM peaked as the release of SmartPLS 2 software came to the scene (Shiau et al., 2019). About the same time, Tenenhaus et al's (2005) article on PLS-SEM's statistical properties was introduced to the mass on its methodological properties. In 2015, Ringle et al. (2015) released the SmartPLS 3 updated software, providing an extension of analysis from its predecessor. It includes advanced supplementary methods and complex model analysis metrics and is complemented with all the necessary primary analysis options.

It is undeniable that the PLS-SEM is used widely in multiple research fields. PLS-SEM, therefore, is much different in its application for the user of PLS software. Users need to not only know what the current PLS software version is but also how to use it (Henseler et al., 2015). The usual software programs for PLS-SEM are SmartPLS, ADANCO, PLS-graph, and PLS graph, while CB-SEM are AMOS, LISREL, Mplus, and EQS (Hair et al., 2017a). As for the software's that were used in the review, ten studies had applied SmartPLS (33.3 percent), nine used the PLS graph (30 percent), two studies conducted the Visual PLS (6.67 percent), and nine others did not state the name of the software they had used. SmartPLS is currently regarded as the most comprehensive software in PLS-SEM application (Sarstedt & Cheah, 2019). The software is designed to allow beginners to use it for a short period of time without having to put much effort into

learning rigorously. Particularly true for basic analyses, SmartPLS software requires intense learning and training for its advanced analyses.

6. Implications

This study provides several implications. Firstly, despite the nature of the article being based on reviews, it presents an embodiment of VC's importance in support of knowledge sharing in e-learning. Since the emergence of the COVID-19 pandemic, the e-learning support system has been the most effective form of teaching and learning for instructors and students. It is imperative that personnel involved in e-learning be prepared for transformation in education (Widyanti et al., 2020). The importance of adopting a proper KM in e-learning is critical for educational management (Shamizanjani et al., 2013), especially for the new norm. Online learning should be structured and systematic to ensure that e-learning is adapted efficiently and effectively. Furthermore, VC studies focusing on KM have become much more significant since the pandemic, which has been supported by information and knowledge digitalization.

7. Limitation of PLS-SEM

According to Dijkstra and Henseler (2015), there are two primary deficiencies in PLS-SEM. Firstly the estimation of PLS-SEM on path coefficients and loadings are only consistent at large. This would lead to the issue of bias due to paths between observed variables and latent variable proxies calculated away from zero, of which the parameter estimates are attenuated between path proxies. Secondly, PLS-SEM does not provide the goodness of fit, making PLS-SEM lack in comparing theories as to the case in CB-SEM. Of these two, the issue of consistency is a more serious problem, which has led to the development of PLS consistent (PLSc).

8. Conclusion

Thirty studies in the virtual KM field were reviewed based on PLS-SEM usage. Articles across top-tier KM journals were taken between the time period of 2009 to 2019 (10 years) were taken. This review of the article using PLS-SEM indicates that the comparison across various disciplines suggests that KM in the virtual field does not fully utilize the function available in PLS-SEM. Compared to other disciplines (marketing or supply chain), KM in the virtual field applies the same or lower reporting standards. Researchers have not fully exploited the capabilities of the PLS method and, to some extent, have applied certain analysis wrongly. Researchers should provide a different reason in the KM discipline for selecting PLS-SEM. The most common reason stated is the dependence on data characteristics of sample size and normality of data. Apart from that, other reasons such as model complexity, theory development, and formative indicators were also given by authors that opted for PLS-SEM.

The PLS-SEM is a preferred method in social science due to reasons such as type of research, small sample size, non-normal sample size and, formative construct. Firstly, assumptions are not stringent compared to CB-SEM, where scale based on nominal, ordinal, interval, and ratio can be applied when interpreted correctly based on the guidelines. Secondly, PLS-SEM can achieve considerable statistical power using a limited sample size and complexity of the model (Reinartz et al., 2009). PLS path modelling is based on the ordinary least square's regression for independent path model

subparts. Hence, the model would have minimal impact on the need for a large sample size (Hair et al., 2017b). Third, PLS-SEM can be ready to measure reflective and formative models. Fourth, the attractiveness of the software in PLS-SEM such as SmartPLS and PLS Graph having user-friendly features and graphical user-interface with multi-option for advanced analyses. Fourth, the PLS-SEM provides user-friendly features and graphical user-interface with multi-option for advanced analyses such as the SmartPLS and PLS Graph software. Based on the current scenario, as studies become more complex, including building a conceptual and theoretical foundation in formatting a particular study, a robust method such as PLS-SEM is needed to facilitate researchers by providing the upper hand in the analysis. Hence, an updated and proper guideline in reporting the PLS-SEM method within a small scope of the study should be advocated and followed by all relevant parties of interest in KM studies.

Author Statement

The authors declare that there is no conflict of interest.

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