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Identifying sustainable warehouse management system indicators and proposing new weighting method

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ABSTRACT

The performance of a sustainable warehouse management system is a multidimensional concept based on the triple bottom line approach. It has been a challenge to identify the key performance indicators for a sustainable warehouse management system and to develop a model for evaluating the direct and indirect indicators. In order to overcome this challenge, this paper describes a method to identify and weight indicators that assess sustainability in a sustainable warehouse management system using structural equation modeling. A comprehensive literature review has been conducted and a questionnaire survey involving experts in the field has been undertaken. A list of 33 key performance indicators for a sustainable warehouse management system has been proposed, and this can be used by policy-makers to appraise the sustainability performance of a sustainable warehouse management system. The proposed robust model can weight indicators and evaluate the total effect of each indicator in incorporating sustainability in a sustainable warehouse management system. The developed method could also be applied to weighting indicators for other industries.

1. Introduction

Over the last decade, there has been continuous pressure for organizations to focus on the sustainability and accountability of a company's performance beyond the border of financial issues. There have been requests to focus more on environmental and social issues by the government, stakeholders and shareholders. Furthermore, there are other sources of pressures, such as societal mandates incorporated into regulations, fear of loss of sales, and decrease of credit and reputation, for a company that has not shown sufficient tangible commitment to sustainability management (Siegel, 2009).

Chen et al. (2017) believed that the majority of studies on warehouse management systems have focused on three factors viz. time, cost and profit. Although their models are practical for industries; environmental and social aspects have not been considered. De Koster and Balk (2008), Kayakutlu and Buyukozkan (2011), Gutierrez et al. (2015), Johnson and McGinnis (2010), Litvak and Vlasiou (2010), Ribino et al. (2018), Hackman et al. (2001), Corinna Cagliano et al. (2011) have looked at warehouse management system from different perspectives when developing performance measurements. However, the proposed indicators focus on economic and efficiency aspects while the social and environmental aspects of warehousing are missing.

There are some other studies that attempt to incorporate other factors apart from economic indicators. He et al. (2017) was developing low-carbon logistics, and a Performance Measurement System (PMS) has been proposed to evaluate low-carbon logistics considering economic, social and environmental performance. However, the proposed indicators are adopted to assess logistics enterprises' performance rather than focusing on warehousing as a whole. Calzavara et al. (2017) evaluated the operational efficiency of order picking in a warehouse by developing economic and ergonomic performance measures. Foroozesh et al. (2018) proposed a multi-criteria decision-making model to evaluate the sustainability of warehouse locations considering three aspects of sustainability to determine the most sustainable warehouse location. Tan et al. (2010) developed a sustainable simulation model focusing on warehouse location, using social and environmental criteria. He developed a balanced scorecard along with a sustainable

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Nomenclature

TBL	Triple Bottom Line
CSR	Corporate Social Responsibility
PMS	Performance Measurement System
SWMS	Sustainable Warehouse Management System
AHP	Analytical Hierarchical Process
DEA	Data Envelopment Analysis
KPIs	Key Performance Indicators
GRI	Global Reporting Initiative
SEM	Structural Equation Modeling
PLS-SEM	Partial Least Square-Structural Equation Modeling
CB-SEM	Covariance Based- Structural Equation Modeling
PLS	Partial Least Square
SW	Sustainable Warehousing
EFA	Exploratory Factor Analysis
AVE	Average Variance Extracted
KMO	Kaiser-Meyer-Olkin
FMM	Federation of Malaysia Manufacturer
CR	Composite Reliability
VIF	Variance Inflation Factor
GOF	Goodness-of-fit

simulation model. However, according to Shafiee et al. (2014), the balanced scorecard is not able to estimate mathematical logic for relationships amongst indicators.

In spite of the fact that researchers have paid attention to sustainable supply chain and green supply chain, the Council of Supply Chain Management Professionals (Council of Supply Chain Management Profession: State of Logistics Report 2013) stated that contrary to the increasing interest in improving efficiency and sustainability of supply chain logistics; incorporating sustainability in warehouse has not received sufficient attention. Neto et al. (2008) and Linton et al. (2007) discussed the importance of integrating sustainability into warehouse operations. They believed companies that are involved in warehousing services have to recognize the necessity of considering sustainability issues in their businesses. A study has been done by Bank and Murphy (2013), in which they have tried to explore the field of sustainable warehousing. Their study can be considered as a early-stage study on Sustainable Warehouse Management System (SWMS) since they have introduced basic sustainability indicators of SWMS considering the three aspects of sustainability.

In order to consider social and environmental aspects along with economic aspect, Nikolaou et al. (2013), Esteves et al. (2012), Presley et al. (2007) and Tschopp (2005) pointed out the usefulness of using Triple Bottom Line (TBL) approach when developing the measurement model of SWMS. He et al. (2017) declared that TBL is the most comprehensive approach to incorporate sustainability, and they highlighted that ignoring even one aspect of TBL would result in managers failing to integrate sustainability. Garriga and Melé (2004) highlighted the contributions of TBL that significantly increase the economic efficiency that encompasses social and corporate sustainability.

On the other hand, incorporating sustainability in the warehouse raises questions about how a manager can appraise the level of sustainability accurately? In today's business, PMS plays a crucial role in managing a system because a system can be managed when it can be measured (Franceschini et al., 2007). Performance evaluation enables managers to develop an effective corrective action plan to decrease or eliminate the weaknesses and empower the strengths of the system to achieve long term competitive advantages and get more market share (Nudurupati et al., 2011). This has a faraway reach unless the appropriate PMS, which is aligned with the SWMS features and objectives are used.

Staudt et al. (2015) studied the literature on performance measurement of a warehouse. They classified the researches based on main warehouse activities; receiving, storage, order picking, shipping and delivery. They pointed out that the majority of studies considered only retrieving and picking activities while 40% of the articles focused on all major activities of the warehouse simultaneously. In another classification, Gu et al. (2007) grouped studies on performance measurement of a warehouse into three types; benchmarking, analytical and simulation methods. Some researchers used a mathematical method such as Russell and Meller (2003), Hwang et al. (2004), Bozer and White (1990) and some others used simulation methods such as Ekren (2011), Hwang and Cho (2006) and Chackelson et al. (2013) while there are some studies under benchmarking group that used Analytical Hierarchical Process (AHP) or Data Envelopment Analysis (DEA) methods such as Chen et al. (2010), Rai et al. (2011) and Johnson and McGinnis (2010).

Although there are several studies about performance measurement of SWMS, the number of studies that comprehensively consider the TBL approach while focusing on the entire warehouse operations is limited and needs to be enriched. The comprehensive and precise indicators to assess the sustainability of SWMS have not been developed, and current indicators cannot cover all angles of sustainability. Hence, the enrichment of the indicators and the method to measure KPIs of SWMS is necessary (Bank and Murphy, 2013). The other challenge that needs more attention is the total effect of each indicator (weight), which constitutes the SWMS (Staudt et al., 2015). By weighting indicators, a manager will be able to calculate the inherent impact of indicators on SWMS, thus enabling them to identify weaknesses and strengths of the system accurately. Although the total effect of each indicator is a powerful tool which gives manager useful insights, it has not received enough attention in the existing literature.

In order to fill up this gap, this research aims to identify a comprehensive KPIs for the entire SWMS considering the TBL approach. The role of the indicators' weight is to express the total effect of each indicator on sustainability in the SWMS. Therefore, to evaluate the level of sustainability accurately and also to develop corrective action plans effectively, it is essential to assign weights to the KPIs. To this end, this study proposes an innovative method to weight qualitative and quantitative indicators without any limitation on the number of criteria. By using that, decision-makers and managers will be able to allocate their resources efficiently in order to increase the level of sustainability in the most cost-effective way.

In Section 2, the research methodology is discussed to show existing methods and how the pool of indicators is created and also to indicate the research framework. A conceptual model for the PMS of SWMS is described in Section 3. In this section, the reliability and validity of the conceptual model have been tested. In Section 4, the second main objective of this study is accomplished by proposing a new method to weight KPIs of SWMS using the Smart Partial Least Square (PLS) software. In Section 5, the case study assesses the applicability of the proposed model. Based on the results, conclusions are given in Section 6. The study concludes with the key findings and proposals for future works.

2. Research approaches

2.1. Method for the derivation of indicators

The current study has used different sources to derive a pool of indicators. Ploos van Amstel and D'hert (1996), proposed performance indicators for warehouse management systems at the tactical and operational levels. Kiefer and Novack (1999), suggested economic indicators of warehouse focusing on order fulfillment, storage, receiving, customer satisfaction, perceived measurement effectiveness, and costs and earnings. Rai et al. (2011) introduced various measures to conduct a carbon footprint study on distribution warehouse building. In order to establish a comprehensive set of indicators for SWMS, indicators that are introduced by peer-reviewed papers are combined with Global Reporting Initiative (GRI). GRI offers qualitative and quantitative indicators that can be applied to evaluate the sustainability of companies considering TBL. This method has been practiced by Krajnc and Glavič (2005a) and Krajnc and Glavič (2005b) to create a composite sustainable development index. An overview of the research framework is shown in Fig. 1, wherein the first three steps, a process has been conducted to identify the KPIs of SWMS. In the first step, the most relevant literature about performance measurement of SWMS has been identified (Table 1). In step 2, a pool of indicators including 239 indicators related to the warehousing and sustainability have been compiled through a wide-ranging literature review. Fifty eight indicators have been refined from the initial indicators, getting reviewed by two experts and one academician which formed the preliminarily list of indicators. In step 3, a questionnaire survey and four rounds of interviews with three academics and three industrial experts have been conducted between May and October 2014 and finally, thirty three KPIs for SWMS have been selected. The duration of interviews varied between 55 and 112 min excluding introduction and including discussion about indicators.

3. Conceptual framework for performance measurement model of SWMS

3.1. Structural equation modeling

Although the first-generation statistical techniques provided the researchers with powerful tools for answering the managerial and theoretical questions, they are not able to assess both measurement properties and test key theoretical relationships at the same time. Furthermore, first-generation techniques are unable to analyze variables that act as the dependent and independent variables simultaneously. Therefore, SEM, the second generation of multivariate analysis is used to overcome the shortcomings of first-generation techniques.

Becker et al. (2012) stated that the majority of researchers rely on first-generation techniques due to the use of the single-item measure, but they identified that the strategic management field turned towards the development of multi-item scales and the use of SEM (Henseler et al., 2009). Partial Least Square-Structural Equation Modeling (PLS-SEM) is recommended where the research objective involves the prediction and development of theory (Hair et al., 2011). Furthermore, in the case of existing formative relations between variables, PLS-SEM is suggested as an alternative and often more appropriate to Covariance Based-Structural Equation Modeling (CB-SEM) (Hair et al., 2011). Therefore, based on the scope of this study and the proposed conceptual model, PLS-SEM is chosen to assess the proposed model.

3.2. Conceptual model

The conceptual model is shown in Fig. 2. This study focuses on a special model containing three orders latent constructs and formative constructs as high-order constructs that can be supported by PLS appropriately (Chin, 1998; Lohmoller, 1988). This conceptual performance measurement model indicates that the aggregation effects of all three aspects of sustainability result in the incorporation of sustainability in the warehouse management system. By using this type of hierarchical model, lower-order constructs are reflectively measured by their indicators, and high-order constructs are formatively measured by their relevant variables (Becker et al., 2012). The other approach incorporated in this study is the repeated indicator approach or superblock approach, in which the manifest variables (indicators) of the first-order constructs are reused to estimate higher-order constructs (Tenenhaus and Vinzi, 2005; Wilden et al., 2013). Apart from variables that compose the proposed conceptual model, the direction of relations between variables has to be discussed. Diamantopoulos and Siguaw (2006) believed that the direction should be based on theory that specifies the content including unobservable and observable variables.

Therefore, to form the inner model, the formative direction has been used to link three unobservable variables (economic, environmental and social) to the SW construct. On the other hand, to

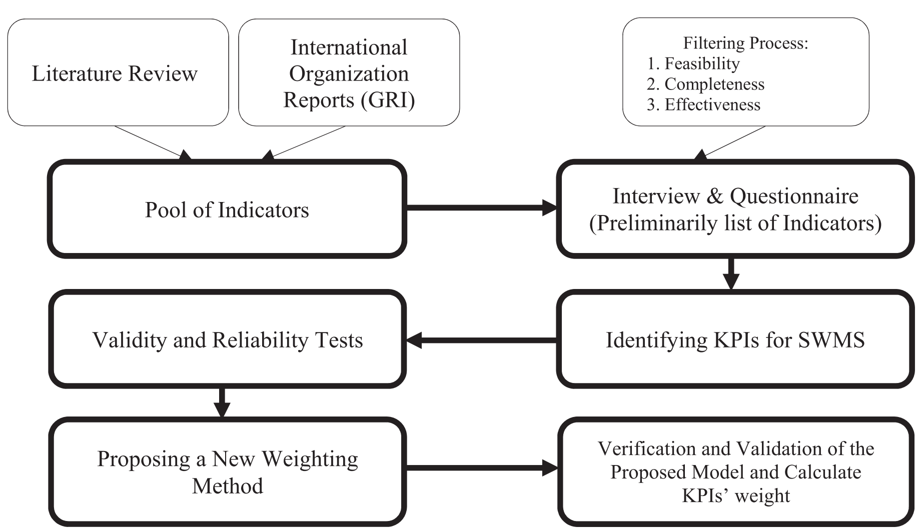

Fig. 1. Schematic of the research framework.

Table 1
Sources of collecting SWMS indicators.

Category	Reference
International existing assessment methods	Sustainability reporting guideline (GRI, 2002)
	United Nation Commission on Sustainable Development, 2001
Academic research papers	Performance indicators in distribution (Ploos van Amstel and D'hert, 1996)
	Warehouse management; automation and organization of warehouse and order picking systems (Hompel and Schmidt, 2006)
	Logistics performance measurement and customer success (Fawcett and Cooper, 1998)
	A reverse logistics social responsibility evaluation framework based on the triple bottom line approach (Nikolaou et al., 2013)

Variable	Definition
SW	Sustainable warehousing
EC	Economic
EN	Environmental
SO	Social
WOP	Warehouse operation performance
EPM	Economic performance measurement
RE	Resources
ECM	Emission waste & environmental commitment
LPDW	Labor practice & decent work
PRS	Product responsibility & society

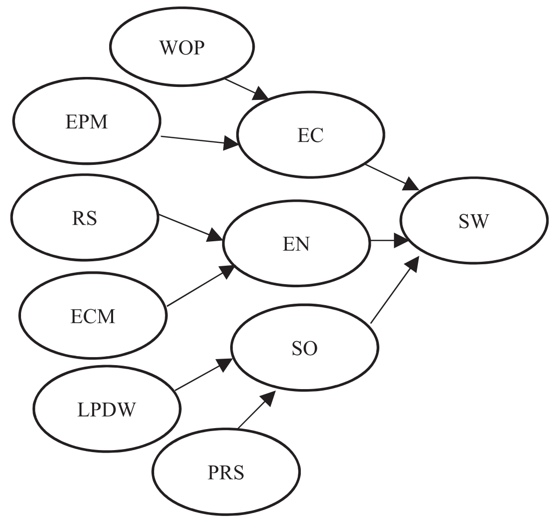

Fig. 2. Conceptual model.

form the outer model, indicators have been linked to relevant variables using reflective relation because increasing the number of variables can cause growth in the number of relevant indicators.

3.3. Validity and reliability of the conceptual model

In order to test the reliability and validity of the model, a pilot study has been conducted in the Automotive Industry to assess the quality of the instrument. The content validity assessment is a rational judgmental process and cannot be done through numerical evaluation (Li et al., 2005). For this purpose, academicians and industrial experts have validated the coverage of the proposed questionnaire as is explained in Section 2. On the other hand, factor analysis is employed to examine the construct validity of the instruments. Therefore, all first-order constructs were analyzed separately by running the Exploratory Factor Analysis (EFA) test (Table 2). In order to test the reliability of measurements, Cronbach's alpha is used. According to Table 2, the first-order construct can be retained, because their EFA is greater than 0.5 and also Cronbach's alpha value exceeds 0.7 which is the minimum threshold as recommended by (Hair et al., 2010). Therefore, all constructs met the requirement of having internal consistency and construct validity. The second and third-order of the proposed model contain formative constructs, and since reliability is not an issue for the formative construct, the reliability test is not applicable for second and third orders. However, there are some other criteria that should be examined to confirm the validity and relation of the whole model. Therefore, Smart PLS software v3.1 was used to assess the relationships and validity of criteria. For this reason, the Average Variance Extracted (AVE) was employed to evaluate the convergent validity of constructs and according to Table 2, all constructs' AVE exceeded 0.5, so the convergent validity of the formative construct was confirmed (Chin, 2010; Hair et al., 2010). Furthermore, to assess the discriminant validity, a cross-loading test for the first-order constructs is applied (Wright et al., 2012). According to Table A.1 (see Appendix A), all indicators loading on their relevant variables possess greater amounts than other variables. Therefore, it can be concluded that indicators have more relation with their relevant construct other than other variables. In addition to the cross-loading test, to assess the discriminant validity, Fornell-Larcker criteria are also used as it is recommended by Hair et al. (2011) and results supported the findings. According to Table 3, the square root of AVE for any first-order construct is higher than the correlation between this construct and the rest of the constructs in the same column and row which confirm the discriminant validity of variables.

Nomological assessment is the next criteria, and according to the Hair et al. (2010) nomological test can be conducted using the correlation matrix. Table A.2 (see Appendix A) shows that the constructs are related to each other and all constructs have a strong relationship with their relevant constructs as proposed in the conceptual model. Apart from relations between constructs, the intended direction of arrows in the conceptual model must be analyzed. According to Table 4, all proposed arrows were supported, and are positively and significantly correlated to their prior constructs. Consequently, the constructs met the requirement of nomological validity by confirming the relations and signs of correlations. Furthermore, to evaluate the sample adequacy, Kaiser-Meyer-Olkin (KMO) test was conducted as it is shown in Table A.3 (see Appendix A). KMO test shows that the overall measure of sampling adequacy is 0.86 which exceeds the minimum acceptable value of KMO (Akter et al., 2013).

According to the results, the proposed model is capable of assessing the sustainability of SWMS using SEM. The next section shows how this model will help decision-makers to weight indicators.

Table 2
Reliability and validity test.

Indicator	EFA Loading	AVE of Constructs	Cronbach's alpha
WOP1	0.92	WOP 0.88	0.971
WOP2	0.95		
WOP3	0.94		
WOP4	0.95		
WOP5	0.92		
WOP6	0.92		
EPM1	0.98	EPM 0.90	0.971
EPM2	0.86		
EPM3	0.96		
EPM4	0.98		
EPM5	0.95		
RE1	0.95	RE 0.93	0.96
RE2	0.95		
RE3	0.94		
RE4	0.94		
RE5	0.91		
ECM1	0.98	ECM 0.89	0.97
ECM2	0.90		
ECM3	0.95		
ECM4	0.90		
ECM5	0.97		
ECM6	0.97		
LPDW1	0.98	LPDW 0.93	0.98
LPDW2	0.97		
LPDW3	0.94		
LPDW4	0.97		
LPDW5	0.96		
LPDW6	0.96		
PRS1	0.98	PRS 0.91	0.97
PRS2	0.94		
PRS3	0.96		
PRS4	0.96		
PRS5	0.91		
EC		0.81	NA
EN		0.86	NA
SO		0.80	NA
SW		0.73	NA

Table 3
Fornell-larcker criteria.

	WOP	EPM	RE	ECM	LPDW	PRS
WOP	**0.938**					
EPM	0.831	**0.949**				
RE	0.792	0.778	**0.962**			
ECM	0.855	0.806	0.886	**0.948**		
LPDW	0.777	0.793	0.841	0.811	**0.967**	
PRS	0.769	0.786	0.656	0.761	0.733	**0.954**

Table 4
Path coefficient evaluation.

Proposed Relations	T Statistics	P-Value
EC→ SW	29.277	0.000
ECM → EN	46.732	0.000
EN → SW	26.484	0.000
EPM → EC	33.596	0.000
LPDW → SO	25.753	0.000
PRS → SO	35.306	0.000
RE → EN	45.384	0.000
SO → SW	29.285	0.000
WOP → EC	27.396	0.000

4. Using smart PLS software to weight identified indicators

In this step, weight or total effect of indicators to compose SW is calculated. According to the proposed structural model, the data consist of J block of observed variable $X_j = \{x_{j1}, \ldots \ldots \ldots \ldots, x_{jkj}\}$ that are related to n unobserved variable. Each X_j constitutes the total meaning of a relevant latent variable ξ with mean zero and variance one. To connect the manifest variable x_{jh} to its related variable, two modes A and B can be used. Each manifest variable x_{jh} increase in mode A or reflective method by the latent variable ξ according to the following equation (Guinot et al., 2001):

$$x_{jh} = \lambda_{jh}\xi_j + \varepsilon_{jh} \tag{1}$$

where x_{jh} is the manifest related to latent variable ξ_j, ε_{jh} is a zero-mean error of the latent variable ξ_j and λ_{jh} is the loading between x_{jh} and ξ_j. In mode B or formative method the latent variable ξ enhances by the manifest variable x_{jh} (Guinot et al., 2001):

$$\xi_j = \sum_h \lambda_{jh}\, x_{jh} + \varepsilon_j \tag{2}$$

where ξ_j is the latent variable produced by x_{jh}, ε_j is the standard error of $x_{jh,}$ and the weight of relation between latent variable ξ_j and x_{jh} is indicated by λ_{jh}. The total effect is a coefficient that Becker et al. (2012) used to find the total effect of the latent variable on second-order constructs. In order to calculate the total effect of the latent variable ξ_j on the major construct, all path coefficient from ξ_j to ξ have to be multiplied together as the total effect of ξ_1 and ξ is shown in Fig. 3.

Where $X_{1_{\xi_1}}$ is a manifest variable (indicator) of latent variable ξ_1 and $L_{X_{1_{\xi_1}}}$ is the loading of the indicator on its variable and β_1 is the path coefficient between ξ_1 as a first-order construct and ξ_2 as a second-order construct. λ_1 also is the path coefficient of ξ_2 and ξ as a major construct or third-order construct. Therefore the total effect of ξ_1 on ξ:

$$\xi = \beta_1 \times \lambda_1 \tag{3}$$

Since model A is used in the measurement model and also considering equations (1) and (3), the total effect of indicator WOP_1 is equal by: $wop_1 = \lambda_{WOP_1} \times WOP + \varepsilon_{WOP_1}$ and also $\mathrm{WOP} = \beta_1 \times \lambda_1$. By substituting 3 in 1, the formula can be summarized as: $WOP_1 = \lambda_{WOP_1} \times (\beta_1 \times \lambda_1) + \varepsilon_{WOP_1}$ if $\varepsilon_{WOP_1} = 0$

$$WOP_1 = \lambda_{WOP_1} \times (\beta_1 \times \lambda_1) \tag{4}$$

For higher-order construct where mode B is applied, the relation between cause and effect variables can be expressed as:

$$\xi^{\parallel} = \sum_{i=1} \beta_i \xi_i^{|} + \zeta_i \tag{5}$$

where $\xi^{\parallel}$ is the higher-order construct and $\xi_i^{|}$ is the lower-order construct that constitutes the $\xi^{\parallel}$, β_i is the path coefficient of $\xi^{\parallel}$ with its lower-order constructs and ζ_i is error. As a set example for EC construct the former formula can be extended as:

$$EC = \sum_{i=1}^{i=2} \beta_i EC_i + \zeta_{EC} \tag{6}$$

If $i = 1$ then $EC_1 = WOP$, else $EC_2 = EPM$.

Other second-order variables can be calculated in the same way. Indeed, for the third-order construct (SW) the formula is:

$$SW = \sum_{j=1}^{j=3} \lambda_j SW_j + \zeta_{sw} \tag{7}$$

where SW is the sustainable warehouse variable, and if $i = 1$ then $SW_1 = EC$, if $i = 2$ then $SW = EN$ else $SW_3 = SO$, ζ_{sw} is error and λ_j is the path coefficient of SW with its lower-order constructs.

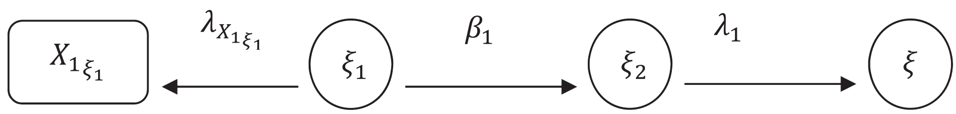

Fig. 3. Total effect of ξ_1 on ξ

Therefore, the weight of each indicator on SWMS can be calculated using the proposed formulas.

5. Case study

5.1. Data collection

A questionnaire survey which aims to weight the SWMS's KPIs has been conducted. The data was collected from Malaysia Automotive Companies due to the importance of the implementation of sustainability in automobile factories' activities (Koplin et al., 2007). The companies were identified from the Federation of Malaysia Manufacturer (FMM) directory 2012 (Jusoh et al., 2008). Respondents were asked to answer the importance level of KPIs by two different questionnaire forms which are named current practice and ideal practice of SWMS. This method is inspired by maturity hybrids or Likert-like questionnaires in which questions are a statement of good practice and the respondent is asked to score the relative performance of the organization on a scale from 1 to n (Mendes et al., 2016). To this end, a questionnaire is developed based on a six-point Likert-type scale, 0 for not applicable (N/A) and rating 1 to 5 for strongly unimportant to strongly important (Parast and Adams, 2012; Shaik and Abdul-Kader, 2014). In the end, 38 pairs of responses were received and finally 35 pairs of questionnaire were useable which hits the minimum number of sample sizes needed to analyze the model using Smart PLS.

It is worthwhile to mention that small sample size is one of the features of Smart PLS software (Henseler et al., 2009; Tenenhaus and Vinzi, 2005). In order to determine the correct sample size, this study follows the rules proposed by Hair et al. (2011). According to the proposed model, the sample size can be at least thirty, and since there are thirty-five correct and completed questionnaires, it exceeds the minimum threshold and can be acceptable. On the other hand, Tongco (2007) asserted that five is the minimum number for the sample size to be reliable in purposing sample; however, Guest et al. (2006) stated that sample size of between six and twelve informants is often sufficient to achieve data saturation for every theme. They emphasized that if the study's goal is to assess the correlation among variables, a sample size of twelve among homogenous individuals should suffice.

Affiliation types of the experts involved in the survey are from industry. 100% of respondents are from Malaysia automotive factories and their suppliers, 62% of companies have more than 250 employees, 79% of companies have been established in automotive industry for more than 10 years, 36% of respondents are high-level executive (C-level) and 38% of them are head of department or first-line manager. 61% of respondents have 5–10 years' experience, 20% have 10–15 years' experience, 16% less than 5 years' experience and 3% have more than 15 years' experience. Furthermore, 81% of respondents are directly related to warehousing and logistics. Among the companies that responded; 30% are manufacturers, 24% are component suppliers, 21% are assembler, 9% are sub assemblers, 16% are the distributor and raw material suppliers.

5.2. Reliability and validity

In order to construct reflective manifest variables, unidimensionality criteria should be assessed prior to conducting the reliability and validity tests. According to Table 5, the unidimensionality is confirmed since Cronbach's alpha of all first-order variables exceeded the threshold value of 0.7 (Schmiedel et al., 2014). Next, to test reliability and validity, three criteria must be assessed according to Fornell (1981). According to Table 5, AVE and Composite Reliability (CR) tests of convergent validity were met by the first-order constructs. Furthermore, the factor loading of all indicators should exceed the required threshold of 0.6 (Gefen and Straub, 2005) and this is fulfilled as it is shown in Table A.4 (see Appendix A).

Moreover, the loading of the reflective indicators on their relevant constructs at the item level should be notably larger than their cross-loading on the other constructs (Wright et al., 2012). According to relationships, the difference of 0.09 is acceptable for item loading and cross-loading; so all items met this requirement (Table A.4). Also, as shown in Table A.5, the discriminate validity of first-order constructs is confirmed (Schmiedel et al., 2014).

After examining the validity and reliability of the first-order constructs, the rest of the constructs at a higher level should be examined in terms of their credibility. At first, indicators' weight was analyzed to show the absolute contribution of the formative indicators to the higher-order constructs (Ringle et al., 2012; Wright et al., 2012). As Table 6 indicates, all weights are considerably high, so it can be inferred that the higher-order constructs are explained by the lower-order constructs. Therefore, the proposed aggregate constructs and their sub-dimensions were confirmed.

The second criterion, adequacy of coefficient R_a^2 was considered to appraisal the relation between higher-order constructs and lower-order constructs (Edwards, 2001; MacKenzie et al., 2011). They stated that to confirm the adequacy of R_a^2 all third and second-order constructs have to be above 0.5. As shown in Table 6, all third and second-order constructs met this requirement, which means almost all variances in the formative indicators are shared with the formative constructs (MacKenzie et al., 2011). Furthermore, multi-collinearity is the third criterion, and it is examined by using Variance Inflation Factor (VIF) (Ringle et al., 2012). Hair et al. (2011) believe that there is no concern regarding multi-collinearity if the thresholds are lower than the cut-off value of 5.0.

According to Table 6, all third and second-order constructs are above 0.5, and none of the first-order constructs exceeds the cut-off of 5.0, so the multi-collinearity cannot be an issue for the second-order constructs which are linked to SW. Although there are some tools to calculate the Goodness-of-fit (GOF) for PLS, there are some challenges in terms of their usefulness and applicability. Hair et al. (2013) identified that GOF is not able to differentiate valid models from invalid ones and does not declare a goodness-of-fit criterion for PLS-SEM. Therefore, GOF has not been assessed in this study.

Table 5
Unidimensionality and first-order constructs validation tests.

	WOP	EPM	RE	ECM	PRS	LPDW
Cronbach's α	0.97	0.95	0.96	0.97	0.96	0.98
AVE	0.87	0.84	0.86	0.86	0.85	0.91
CR	0.98	0.96	0.97	0.97	0.97	0.98

Table 6
Higher-order constructs validation.

Higher order constructs code	Lower order constructs code	Weight	Significance	VIF	Adequacy coefficient R_a^2
EC	WOP	0.67	$p < 0.00001$	1.61	1.00
	EPM	0.43	$p < 0.00001$	1.61	
EN	RE	0.47	$p < 0.00001$	1.99	1.00
	ECM	0.61	$p < 0.00001$	1.99	
SO	LPDW	0.64	$p < 0.00001$	1.63	1.00
	PRS	0.46	$p < 0.00001$	1.63	
SW	EC	0.33	$p < 0.00001$	2.33	1.00
	EN	0.38	$p < 0.00001$	3.52	
	SO	0.37	$p < 0.00001$	3.09	

5.3. Hypothesis testing

First, Smart PLS was ran to estimate the measurement model and inner model, then the significance of each relation was examined by running bootstrapping. In this study, 5000 subsamples from the original sample with replacement were created by Smart PLS software to run the bootstrapping as suggested by Hair et al., (2011). The measurement model was used to assess the relationship between indicators and their relevant construct (F. Hair Jr et al., 2014). As shown in Table 7, all indicators are highly related to their relevant variables and all are well above 0.7, which indicates a significant relationship between indicators and their related constructs. Regarding the inner model, the results provide evidence to confirm the proposed hypothesizes as shown in Table 8. The results shows that the economic, social and environmental variables have a significant relationship with SWMS and simultaneously they have significant relation with their sub-variables in first-order layer, therefore all nine hypothesizes are supported. Now the model can be used to calculate the weight of each indicator on SWMS. To this end, next section shows how to calculate the total effect of indicators using the given formulas in section 4.

5.4. Total effect (weight) of indicators on SW

To calculate the total effect of indicators the Smart PLS software and also formulas as described in section 4 have been used. This study assumes that error (ε) is equal to zero, so based on the proposed structural model the weight of each indicator such as WOP_1 can be calculated as follows:

$$WOP = \beta_1 \times \lambda_1 \rightarrow WOP = 0.671 \times 0.332 = 0.222$$

$$WOP_1 = \lambda_{WOP_1} \times (\beta_1 \times \lambda_1) \text{ then } WOP_1 = 0.954 \times 0.222 = 0.211$$

Table 7
Factor loading of all indicators.

Construct	Indicator	Definition	Factor Loading	Significance
WOP	WOP1	Increasing time efficiency of receiving operation and shipping operation	0.95	$p < 0.00001$
	WOP2	Decreasing cost across warehouse operation	0.93	$p < 0.00001$
	WOP3	Increasing accuracy in time, quality and quantity of full-field order	0.91	$p < 0.00001$
	WOP4	Increasing utilization of storage capacity	0.93	$p < 0.00001$
	WOP5	Improving through time of order picking	0.93	$p < 0.00001$
	WOP6	Improving throughput time of loading and unloading	0.90	$p < 0.00001$
EPM	EPM1	Direct and indirect economic value generated and distributed	0.90	$p < 0.00001$
	EPM2	Determining risks and opportunities for the organization's activities due to the climatic changes	0.97	$p < 0.00001$
	EPM3	Financial assistance received from government and tax reduction	0.92	$p < 0.00001$
	EPM4	Ratio of standard entry-level wage to local minimum wage with considering gender	0.87	$p < 0.00001$
	EPM5	Ratio of spending on local supplier to non-local supplier	0.90	$p < 0.00001$
RE	RE1	Ratio of recyclable material used to total material used	0.92	$p < 0.00001$
	RE2	Reduction of energy consumption	0.97	$p < 0.00001$
	RE3	Ratio of total recycled water consumption to total water consumption	0.92	$p < 0.00001$
	RE4	Reduction in energy requirement of products and services	0.95	$p < 0.00001$
	RE5	Decreasing the impact of the organization on biodiversity and habitat	0.83	$p < 0.00001$
ECM	ECM1	Reduction the amount of direct and indirect and other relevant greenhouse gas (GHG) emission	0.92	$p < 0.00001$
	ECM2	Reduction in percentage of waste and effluent (all kinds of disposal)	0.92	$p < 0.00001$
	ECM3	Attempts to mitigate the environmental impact of product and services, packaging and transportation	0.91	$p < 0.00001$
	ECM4	Percentage of product sold with recycle packaging material	0.97	$p < 0.00001$
	ECM5	Ratio of number of grievances about the violation of environmental laws that are resolved by formal mechanism to total grievances	0.91	$p < 0.00001$
	ECM6	Total environment protection cost and investment per year	0.91	$p < 0.00001$
LPDW	LPDW1	Total number of new employee hired by age group, gender and religion	0.97	$p < 0.00001$
	LPDW2	Benefit applicable for full-time employee, by significant location of operation	0.96	$p < 0.00001$
	LPDW3	Minimize the number of changes affecting the working hours, which are outside the collective agreement	0.93	$p < 0.00001$
	LPDW4	Average of training hours per employee per year	0.97	$p < 0.00001$
	LPDW5	Percentage of employee receiving regular performance and career development reviews	0.91	$p < 0.00001$
	LPDW6	Employee turnover by age, gender and religion	0.97	$p < 0.00001$
PRS	PRS1	Minimizing the number of complaints of sexual discriminations and labor disputes	0.97	$p < 0.00001$
	PRS2	Minimizing the number of customer complaints (quality, warranty and repair)	0.90	$p < 0.00001$
	PRS3	Decreasing the type and rate of injuries, occupational diseases, the total number of work-related facilities, breakdown and lost days	0.95	$p < 0.00001$
	PRS4	Number of community services projects and their impact on the local community	0.93	$p < 0.00001$
	PRS5	Minimizing the number of mismanagement, corruption, malpractice, punishment reported for the year	0.83	$p < 0.00001$

Table 8
Estimated model using Smart PL.

Path	Parameter estimated	Sample mean	Standard Error	T statistics	P-value Sign level <0.01
WOP → EC	0.760***	0.678	0.061	11.039	$p < 0.00001$
EPM → EC	0.430***	0.424	0.039	11.132	$p < 0.00001$
RE → EN	0.460***	0.471	0.026	18.394	$p < 0.00001$
ECM → EN	0.612***	0.608	0.028	22.130	$p < 0.00001$
LPDW → SO	0.640***	0.645	0.036	18.073	$p < 0.00001$
PRS → SO	0.460***	0.461	0.026	18.148	$p < 0.00001$
EC → SW	0.330***	0.331	0.037	8.880	$p < 0.00001$
EN → SW	0.380***	0.338	0.029	13.629	$p < 0.00001$
SO → SW	0.370***	0.375	0.028	13.624	$p < 0.00001$

The weights of other indicators can be calculated using the same procedure and the final results are shown in Fig. 4. Based on the results, EMP2 has the highest loading among indicators of EC so decision-makers might have decided to allocate resources to EMP2. However, among indicators that describe EC, WOP1 has the highest total effect on EC. Therefore, WOP1 has the highest impact on SW compared to other indicators of EC. Moreover, among indicators in the first-order layer that describe environmental variables, ECM4 has the highest weight to form SW. Regarding the social aspect of SW, LPDW has the strongest relationship with SW and also LPDW1 has the highest weight to construct SW.

6. Conclusions

Sustainability assessment of SWMS is a highly significant task and it is urgently needed. There is plenty of challenges for policy-makers due to the diversity of sustainability and the complexity of incorporating and measuring sustainability in SWMS. During this study, a comprehensive literature review has been conducted to identify the status of the existing PMS of SWMS. A pool of indicators is made by using the most relevant literature on performance measurement of SWMS. Then, two experts and one academician have formed the initial list of indicators. In the last step of indicators purification, during four rounds of review and interview with three experts and three academicians, some non-related indicators to SWMS have been deleted, some indicators that overlap are merged which resulted in thirty-three KPIs for SWMS.

A full survey has been conducted where 80% of the questionnaires have been received while only 73% were useable. Then, the reliability of the questionnaire has been evaluated using Cronbach's alpha where the value achieved is 0.95, and the AVE achieved is more than 0.84. Then a novel approach for developing measurement model is developed using SEM in which the level of sustainability incorporated in SWMS can be calculated using a hierarchical model. The hierarchical component model with three layers can avoid extreme individual preference in decision making. The novel method has been implemented in automotive companies in Malaysia to calculate the KPIs' weight.

The review of current methods indicated that a comprehensive set of KPIs that covers three aspects of the TBL approach in SWMS is lacking. More specifically, the proposed measurement method should ensure that they can assess all three aspects of sustainability in the warehouse management system simultaneously using indirect and direct indicators. Furthermore, measurement models should be able to calculate sustainability of the entire SWMS rather than focusing only on one or few operations. This feature can help managers and decision-makers to have a clear picture of the overall sustainability incorporated in SWMS. Moreover, since loading volume and the total effect of indicators can be varied due to the hidden influence of indicators, the proposed model should be able to calculate the total effect of each indicator.

Holistic analysis of this research added to existing studies has identified thirty-three KPIs for SWMS. The proposed model is able to weight qualitative and quantitative indicators in a way that weight magnitude describes the total effect of each indicator. Moreover, the model can calculate the weight of any number of indicators. Apart from weighing indicators, the proposed model extends the application of TBL to the entire SWMS. This allows decision-makers and managers to decrease environment and social issues when the economic impacts of SWMS are being considered. This model is suitable and applicable in the majority of countries especially those that do not consider cap-and-trade policy or any

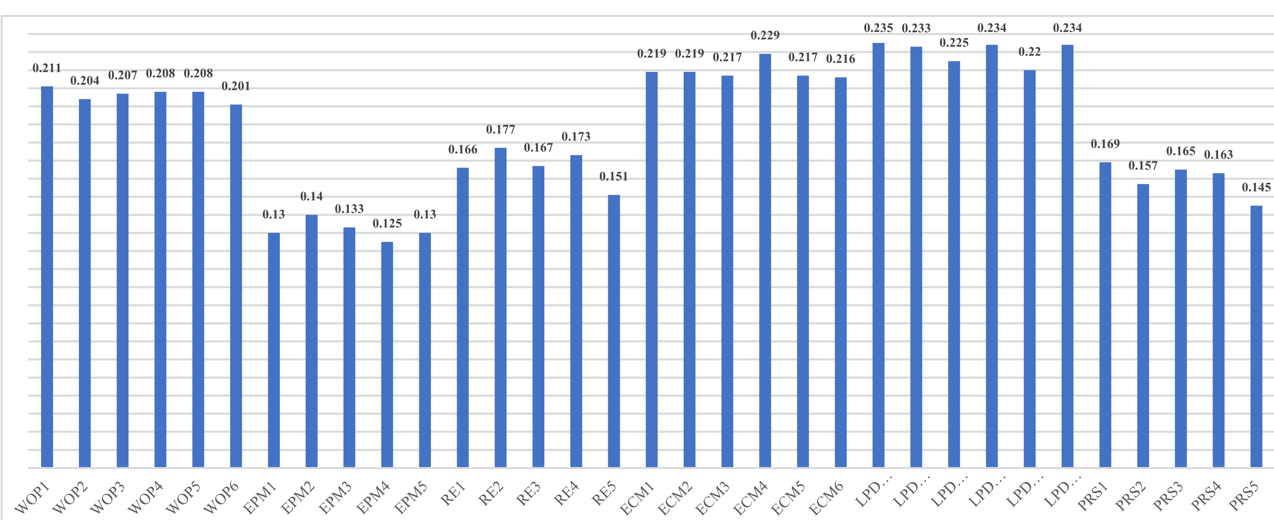

Fig. 4. Weight of each indicator to compose SW.

country that cap-and-trade has not been fully legalized yet.

As far as the costs of incorporating sustainability are concerned, decision-makers and managers have been trying to incorporate sustainability with minimum influence on expenses. By using the proposed model, decision-makers and managers will be able to allocate their resources efficiently in order to increase the level of sustainability in SWMS in a very cost-effective way. This study can help the automotive industries to develop more effective sustainability strategies and motivate managers to assess the level of sustainability continuously.

Further study is necessary in order to identify a set of KPIs for other sections of the supply chain since each section has its own criteria. Therefore, calibrating the KPIs for other segments of the supply chain can be studied in the future. Due to the different features of each industry, generalizing the proposed PMS to other industries is another line for future work. Moreover, the programming of an application would significantly improve the proposed model which can be examined in the future.

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Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2019.119190.

Appendix A

Table A.1
Cross loading.

Indicator	WOP	EPM	RE	ECM	LPDW	PRS
WOP1	**0.924**	0.760	0.660	0.795	0.649	0.693
WOP2	**0.952**	0.743	0.723	0.753	0.675	0.660
WOP3	**0.943**	0.754	0.848	0.870	0.841	0.784
WOP4	**0.953**	0.856	0.828	0.879	0.837	0.828
WOP5	**0.924**	0.714	0.671	0.749	0.662	0.642
WOP6	**0.929**	0.738	0.710	0.755	0.694	0.684
EPM1	0.816	**0.982**	0.806	0.840	0.800	0.802
EPM2	0.658	**0.859**	0.572	0.578	0.607	0.571
EPM3	0.791	**0.961**	0.752	0.790	0.746	0.775
EPM4	0.816	**0.987**	0.764	0.812	0.770	0.772
EPM5	0.850	**0.951**	0.775	0.780	0.822	0.790
RE1	0.761	0.757	**0.961**	0.853	0.818	0.648
RE2	0.727	0.708	**0.954**	0.870	0.810	0.599
RE3	0.747	0.737	**0.955**	0.860	0.818	0.636
RE4	0.813	0.791	**0.952**	0.839	0.811	0.675
RE5	0.762	0.750	**0.988**	0.838	0.797	0.599
ECM1	0.877	0.803	0.896	**0.981**	0.785	0.749
ECM2	0.775	0.704	0.723	**0.904**	0.633	0.656
ECM3	0.820	0.775	0.873	**0.959**	0.729	0.730
ECM4	0.701	0.731	0.754	**0.900**	0.739	0.719
ECM5	0.858	0.798	0.904	**0.972**	0.879	0.742
ECM6	0.824	0.768	0.874	**0.972**	0.834	0.734
LPDW1	0.739	0.762	0.816	0.772	**0.983**	0.725
LPDW2	0.748	0.747	0.827	0.801	**0.973**	0.705
LPDW3	0.754	0.870	0.875	0.768	**0.941**	0.715
LPDW4	0.790	0.817	0.857	0.827	**0.978**	0.715
LPDW5	0.774	0.783	0.776	0.773	**0.963**	0.681
LPDW6	0.704	0.709	0.814	0.762	**0.962**	0.707
PRS1	0.733	0.761	0.599	0.738	0.677	**0.984**
PRS2	0.756	0.831	0.748	0.748	0.811	**0.966**
PRS3	0.790	0.752	0.688	0.801	0.746	**0.961**
PRS4	0.719	0.719	0.633	0.728	0.700	**0.948**
PRS5	0.656	0.673	0.422	0.596	0.529	**0.908**

Table A.2
Correlation Matrix.

	EC	ECM	EN	EPM	LPDW	PRS	RE	SO	SW	WOP
EC	**1.00**									
ECM	0.870	**1.00**								
EN	0.873	0.976	**1.00**							
EPM	0.949	0.806	0.817	**1.00**						
LPDW	0.820	0.811	0.849	0.793	**1.00**					
PRS	0.812	0.761	0.735	0.786	0.733	**1.00**				
RE	0.821	0.886	0.966	0.778	0.841	0.656	**1.00**			
SO	0.876	0.847	0.858	0.848	0.949	0.910	0.816	**1.00**		
SW	0.959	0.942	0.955	0.911	0.913	0.855	0.911	0.952	**1.00**	
WOP	0.964	0.855	0.851	0.831	0.777	0.769	0.792	0.830	0.922	**1.00**

Table A.3
KMO Test.

Variable	KMO
WOP	0.86
EPM	0.84
RE	0.88
ECM	0.88
LPDW	0.83
PRS	0.87

Table A.4
Cross loading.

Indicator	WOP	EPM	RE	ECM	LPDW	PRS
WOP1	**0.95**	0.68	0.58	0.71	0.51	0.62
WOP2	**0.93**	0.58	0.54	0.70	0.47	0.67
WOP3	**0.92**	0.57	0.75	0.81	0.74	0.74
WOP4	**0.93**	0.52	0.64	0.77	0.65	0.71
WOP5	**0.93**	0.52	0.59	0.74	0.56	0.73
WOP6	**0.91**	0.54	0.58	0.69	0.55	0.64
EPM1	0.61	**0.91**	0.45	0.45	0.45	0.45
EPM2	0.59	**0.98**	0.37	0.47	0.40	0.36
EPM3	0.56	**0.93**	0.34	0.44	0.36	0.43
EPM4	0.56	**0.87**	0.39	0.38	0.20	0.26
EPM5	0.49	**0.91**	0.17	0.37	0.37	0.29
RE1	0.61	0.42	**0.92**	0.66	0.69	0.53
RE2	0.67	0.44	**0.98**	0.72	0.78	0.56
RE3	0.56	0.38	**0.92**	0.62	0.72	0.39
RE4	0.64	0.32	**0.96**	0.69	0.69	0.50
RE5	0.54	0.16	**0.83**	0.55	0.42	0.32
ECM1	0.70	0.43	0.68	**0.93**	0.64	0.66
ECM2	0.72	0.39	0.57	**0.93**	0.57	0.59
ECM3	0.69	0.38	0.67	**0.92**	0.68	0.58
ECM4	0.73	0.37	0.68	**0.97**	0.69	0.66
ECM5	0.74	0.48	0.65	**0.92**	0.73	0.67
ECM6	0.81	0.55	0.65	**0.91**	0.71	0.61
Indicator	WOP	EPM	RE	ECM	LPDW	PRS
LPDW1	0.64	0.43	0.76	0.72	**0.98**	0.63
LPDW2	0.59	0.36	0.64	0.66	**0.97**	0.60
LPDW3	0.53	0.31	0.63	0.60	**0.94**	0.57
LPDW4	0.67	0.47	0.74	0.74	**0.97**	0.64
LPDW5	0.56	0.31	0.64	0.71	**0.91**	0.49
LPDW6	0.57	0.35	0.68	0.70	**0.97**	0.61
PRS1	0.75	0.39	0.48	0.67	0.57	**0.97**
PRS2	0.69	0.44	0.48	0.58	0.65	**0.91**
PRS3	0.74	0.37	0.58	0.71	0.65	**0.95**
PRS4	0.63	0.34	0.53	0.66	0.60	**0.94**
PRS5	0.56	0.23	0.19	0.47	0.32	**0.84**

Table A.5
Discriminate validity of first-order constructs (Fornell-Larcker criterion).

Constructs	WOP	EPM	RE	ECM	LPDW	PRS
WOP	**0.93**					
EPM	0.61	**0.92**				
RE	0.65	0.38	**0.92**			
ECM	0.79	0.46	0.70	**0.93**		
LPDW	0.62	0.39	0.72	0.72	**0.96**	
PRS	0.74	0.39	0.62	0.68	0.62	**0.92**

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