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Data-driven sustainable supply chain management performance: A hierarchical structure assessment under uncertainties

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ABSTRACT

This study contributes to the literature by assessing data-driven sustainable supply chain management performance in a hierarchical structure under uncertainties. Sustainable supply chain management has played a significant role in the general discussion of business management. While many attributes have been addressed in prior studies, there remains no convincing evidence that big data analytics improve the decision-making process regarding sustainable supply chain management performance. This study proposes applying exploratory factor analysis to scrutinize the validity and reliability of the proposed measures and uses qualitative information, quantitative data and social media applied fuzzy synthetic method-decision making trial and evaluation laboratory methods to identify the driving and dependence factors of data-driven sustainable supply chain management performance. The results show that social development has the most significant effect. The results also indicate that long-term relationships, a lack of sustainable knowledge or technology, reverse logistic, product recovery techniques, logistical integration, and joint development are the most effective criteria for enhancing sustainable supply chain management performance. The theoretical and managerial implications are discussed.

1. Introduction

Sustainable supply chain management (SSCM) has attracted significant attention amongst academics and practitioners for balancing the triple bottom line (TBL) in supply chain networks (Dubey et al., 2017a,b). Wu et al. (2017) argued that market changes aimed at sustainable development caused supply chain risks in the industry. These risks can be identified in social media, quantitative data and qualitative information (denoted as big data), but practitioners are incapable of managing this information to address customer needs and environmental requirements (Wu et al., 2017). This study focuses on the Taiwanese textile industry, which produces a large quantity of products to meet customer needs globally, and addresses sustainable development in many countries (Diabat et al., 2014a,b). The industry is located in the global supply chain network due to the goods distribution channels, and hence, services have become complex, and subsequently, the socio-environmental-economic conditions have become a major attribute of supply chain performance (Dubey et al., 2017a,b). The business environment has incurred the uncertainties that generate the need for firms to promote their sustainable development and social impact and remain competitive (Zailani et al., 2012; Walker and Jones, 2012; Ahi and Searcy, 2013; Diabat et al., 2014a,b). Hence, data-driven SSCM performance must be assessed to model the structure.

In reality, big data are a source of value creation and offer a competitive advantage because data enable the recognition of trends in performance, support operational processes and facilitate control (Avelar-Sosa et al., 2014; Yu et al., 2018). For instance, Hazen et al. (2014) discussed whether big data are employed to improve the results of operations and finance. Big data drive changes in SSCM performance in intensive markets. Akter et al. (2016) emphasized that big data analyses have a huge impact on enhancing the performance of firms. The application of big data and

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the imperative for associated big data capabilities challenged traditional institutional arrangements, roles, practitioners and social structures of supply chain functions to procedures and data management (Braganza et al., 2017; Shah et al., 2017; Wang et al., 2016). Assessing SSCM is an important issue, and best-practice firms use big data resources to improve performance (Badiezadeh et al., 2017; Seuring, 2013). Yu et al. (2018) proposed that the data-driven supply chain has a positive effect on supply chain capabilities in information exchange, coordination, activity integration and responsiveness. However, there is a limited understanding of how data-driven SSCM affects changes in functioning and performance (Roβmann et al., 2017).

Prior study has studied this structure and its attributes in the manufacturing industry by adopting information that possesses qualitative and quantitative features (Tseng, 2016; Wu et al., 2017). Still, studies have proposed many SSCM drivers and engaged with empirical methods, either qualitative information or quantitative data, to create theoretical frameworks (Binder and Edwards, 2010; Soltani et al., 2014). Tseng (2016) noted that clarity on what composes SSCM attributes and how to best attain them is lacking. In addition, few studies have concerned the influence of social media in making decisions about firms and collecting qualitative and quantitative information in the decision-making process (Distaso and McCorkindale, 2013; Drouin et al., 2015; Tseng, 2016). Moreover, to assist firms in diagnosing SSCM performance, there is an essential need to classify, evaluate and examine these varied data sources (Hallikas et al., 2004; Peck, 2005; Sodhi et al., 2012). Hence, this study attempts to aggregate various data with the aim of assisting decision-making by conducting a hierarchical structure assessment of a series of attributes to achieve data-driven SSCM performance. In addition, there are many attributes addressed in prior studies. Hence, the objectives of this study are as follows:

1. What are the valid and reliable attributes of data-driven SSCM performance?
2. What are the attributes that enhance data-driven SSCM performance in a hierarchical structure?

This study applies exploratory factor analysis (EFA) to confirm the validity and reliability of the proposed measures. The fuzzy synthetic method-decision making trial and evaluation laboratory method (FSM-DEMATEL) address the hierarchical structure using qualitative and quantitative measures, respectively. In addition, we acquire social media information on Google trends and transformed the keywords into a comparable scale. This study provides a set of valid and reliable SSCM attributes and analyzes data-driven SSCM performance in a hierarchical structure. Through the identification and structuring of a set of attributes, the study presents data-driven SSCM performance and big data in the Taiwanese textile industry, leading to a comprehensive look that leads firms to greater competitive advantage in the industry.

The study is organized into six sections; the first is an introduction of SSCM and big data. In the second section, this study presents the literature on SSCM and big data, introducing the aspects and criteria of the methodology. In the second section, this study presents the literature on these aspects and proposes the measurement criteria. The third section more clearly explains the methodology used. The results are analyzed in the fourth section. The fifth section discusses the implications. Finally, the conclusions and limitations are addressed.

2. Literature review

This section discusses SSCM performance, effects of big data on SSCM performance and the proposed method.

2.1. SSCM performance

The adoption of innovation within the firm's value chain is important to SSCM performance (Lin and Tseng, 2016). Seuring and Müller (2008) emphasized the need to enhance cooperation along supply chain networks to achieve a sustainable development goal. Through SSCM assessments concentrate on adding value to conquer the challenges of low-cost rival campaigns, it is essential to drive products or services into the rival market. Despite the stresses of environmental issues and the consequent increasing demand for information, most firms still have limited knowledge on the environmental impacts of and social developments in their supply chain networks (De Camargo Fiorini et al., 2017). Moreover, firms must address stakeholders systemically from various aspects, including the attributes of sustainability (Engert et al., 2016; Linnenluecke et al., 2009; Tseng, 2017). Lin and Tseng (2016) suggested that stakeholders should assume their roles within the supply chain to guarantee sustainable development.

For instance, Delmas and Toffel (2004) recommended that firm competitiveness of a firm, economic benefits and better social responsibility among the public can be generated by proactive sustainability. Tseng et al. (2015) presented a sustainable development model to express the numerous attributes related to internal and external attributes, which assist all operational processes. Wu et al. (2016) proposed an extended and quantitative method to promote the understanding of SSCM and evaluate its performance. The firm increases sustainable performance by improving productivity and efficiency in SSCM performance; specifically, reverse logistics have a significant impact on the environment when reusing materials, which can reduce the negative effects on the environment (Turrisi et al., 2013). Peña et al. (2018) suggested a need and an opportunity to combine multiple attributes and operational risk aspects. Moreover, by engaging stakeholders such as consumers, firms address potential stress and gain an advantage of stakeholder knowledge (Pagell and Wu, 2009). However, various SSCM attributes require multi-functional operations to attain competitive advantages over rivals and numerous aspects and criteria to assist in the achievement of competitive change (Su et al., 2015).

Still, the volume of information and data available to firms has been continuously growing due to the utilization and diffusion of diverse disruptive digital information technologies (Roβmann et al., 2017). However, few prior studies have offered a reliable structure to address strategic formulation and practices. Hence, firms' managers, scholars and researchers must consider the changes that transform how firms are administrated and alter the economies and communities in which they operate (Raguseo, 2018). Prior studies have demonstrated the importance of strategic direction based on competitive advantage executed through operations. However, the operational attributes possess qualitative and quantitative features. Various social media sources are public information and are employed in the decision-making process (Tseng, 2016). Hence, the various types of data need to be included to increase SSCM performance.

2.2. Big data on SSCM performance

Big data are used to create exponential growth and data availability, and big data have become important to business and society, converting the landscape for the policy and study of socioeconomic considerations and for managing business and decision-making. The dynamic and digitized data on firms' activities must be properly analyzed to help reveal trends and monitor economics, the environment and social impact. Big data provide benefits of more focused products and services in advertising and marketing, generating better economic results and more acceptable and sustainable products and services (Blazquez and Domenech, 2017; LaBrie et al., 2017). The big data approach includes distributing the information on a firm's websites, including sales growth and business activities, such as technology adoption strategies, innovation and study and development (Blazquez and Domenech, 2017). Best-practice firms utilize big data resources to strengthen their performance.

Bonds-Raacke and Raacke (2010) determined that big data, especially social media, are used to share personal information, inform others about social activities and events and attain knowledge. Engert and Baumgartner (2015) employed qualitative information to address the conditions needed for effective sustainability around strategic formulation and practices. Tan et al. (2015) illustrated the profits of data integration from various sources, including data from internal consumers, social media and multimedia to produce innovative products. Tseng (2017) examined how to use qualitative, quantitative and social media information scales to benchmark corporate sustainability and presented a decision-making process that combines the collected quantitative and qualitative information associated with social media. Previous studies have frequently utilized qualitative and quantitative methods, survey-based instruments or traditional statistical techniques (Dubey et al., 2017a,b; Tseng, 2017).

Big data have a special opportunity to make sense to firms and provide firms with the ability to deal with socio-economic issues in an improved way and then reduce the costs of taking uncontrollable risks based on imprecise qualitative thinking. The power of big data is typically related to prophetic analytics that use statistical knowledge to forecast future events and plays a crucial role in altering and improving supply chain network functions. Big data drives SSCM performance and are driven by changes in SSCM performance.

2.3. Proposed method

The DEMATEL was presented in Geneva in 1973 to address complex and uncertain issues (Shieh et al., 2010). The method is used to convert the interrelationship between the cause and effect criteria from a contingent to a justified model of the selected system (Dalalah et al., 2011). The DEMATEL method is a structural model that illustrates casual relations among the complicated real-world attributes. This method is better than the traditional approaches because it enables the discovery of the interrelationships among criteria. Ranking the criteria is a way to discover the interrelationships and reveal the intensity of their effects on individual criteria. In addition, the disadvantage of the DEMATEL is that it is unable to address the hierarchical structure, and the interrelationships are usually addressed in linguistic preferences and are vague in crisp value. Hence, fuzzy set theory is utilized to eliminate the imprecision problem and information uncertainties (Tseng et al., 2018a). In particular, the FSM can address the hierarchical structure (Tseng et al., 2018b).

Prior studies used quantitative, quantitative information and survey-based SSCM approaches. Diabat et al. (2014a,b) identified influential enablers of SSCM using Interpretive Structural Modeling. Tan et al. (2015), based on the deduction graph technique, revealed that the suggested data analysis approach enables firms to utilize big data to obtain a competitive advantage by promoting their supply chain innovation capabilities. Akter et al. (2016) applied partial least squares to assess firms' performance improvement by using big data analytical competence and business strategy alignment. Boon-itt et al. (2017) used the Q-sort method to establish and verify the measurement scales for the concepts SSCM processes and competences. In addition, studies have explored the facets of big data and confirmed that big data are affected by firms' strategic formulation and by the base for building capabilities in the supply chain networks. However, there remains a lack of data on multi-attribute decision making in assessing SSCM performance. This study attempts to apply the FSM-DEMATEL method to present data-driven SSCM performance attributes.

2.4. Proposed measures

SSCM refers to the creation of synchronized supply chains through voluntary incorporation with the main inter-systems of firms in order to encourage efficient and effective management among the resources, information and capital flows associated with the acquisition, manufacture and distribution of products or services; ultimately, it aims to fulfill stakeholder requirements and attain firm benefits, competitiveness and resilience over the short and long terms (Hassan et al., 2017). SSCM performance has been proposed in many practical models and evaluation structures (Chaabane et al., 2012). These attributes serve a critical function in screening suppliers and TBL interrelationships simultaneously (Lee et al., 2009; Tseng et al., 2018b). Hence, this study proposes 26 criteria to construct four aspects to measure processes: economic benefits, environmental impacts, social development and operational risk.

Economic benefits are the fundamental condition of economic development; therein, infrastructures have a significant influence on the regional economic system (Sun and Cui, 2018). Firms must pursue good economic performance by tracking the operational functions of product consumption and waste generation (Tseng at al., 2018). Recent developments in the global economic environment require firms to take reconstruction and reorganization into account to promote their business and profit and to maintain their competitiveness within the market (Zailani et al., 2012; Lin and Tseng, 2016). Several previous studies demonstrated the effect of economic aspects on firms' sustainability (Tseng, 2007). For example, strategic supplier collaboration (C1) enables commercialization and guarantees that innovative technologies can be easily accessed by regional and lower-tier suppliers in the supply chain. Economic stability (C2) indicates that modern firms that launch SSCM have better performance than firms that rely on traditional supply chains during economic crises because the former possess the feature of decisive drivers. Logistics optimization (C3) represents optimizing the velocity, path, burden and the character of transportation; the utilization of substitute energies to replace the fossil fuels; and reverse logistics, which significantly promote the profit margin and greenhouse gas emission control of the firm. Corporate strategy and commitment (C4) provide a precise strategic-level policy to couple strategic-level teams with firms' tactical and operational levels, which is necessary for launching sustainable development practices. Logistical integration (C5) is the direct effect of a firm's planning and predictions on its suppliers and customers. Joint development (C6) contributes to improving sustainable performance through collaboration. Technological integration (C7) must be collaborative to promote sustainability performance (Mathivathanan et al., 2018).

Environmental impacts refer to the ability to be sustainable over time, and to achieve sustainable development, a firm must create the environmental situation for a globally stable system that can benefit humans (Ivascu et al., 2015; Ramudhin et al., 2009). During the past twenty years, environmental issues have compelled the manufacturing industry to progressively comply with green directives. These practices decrease firms' negative environmental impacts and improve the quality of the natural environment. Green directives impel firms not only to increase their competitiveness but also to begin a transformation toward corporate sustainability (Tseng, 2017). Tseng (2013) and Tseng et al. (2018) proposed several indicators and restraints to emphasize environmental aspects in terms of production and disposal, such as green product design that enables decomposition (reused or recycled non-harmful materials). Thus, several studies proposed reverse logistics using product recovery techniques (C8), reuse, recycling and remanufacturing to reduce the negative impacts on the environment. Collaborating with suppliers (C9) to create environmentally friendly products is also an important practice for firms to consider. Green packaging (C10), including adopting new renewable materials, can assist firms attain the minimum usage of resources. The effective use of by-products (C11) indicates that secondary products are efficiently utilized. Environmental awareness training (C12) informs management, employees and communities about the practices promoting environmental sustainability. Environment conservation (C13) involves increasing the accuracy of demand prediction, investing in carbon emission reduction technology, participating in joint distribution, employing the cross-docking web, promoting energy efficiency, and integrating an ecological design with extensive recycling networks. Green warehousing (C14) is used to address the issues of green energy resource consumption and strategies. Green product design (C15) develops green products to tackle environmental issues through the innovative design of products and has received increasing attention from governments, industries and customers worldwide, which is different from traditional end-of-pipe control (Wu et al., 2010; Tseng et al., 2014).

Social development is used to improve the social performance among the supply chain; therefore, current theoretical developments become the basis of future empirical studies (Yawar and Seuring, 2018). Sustainable services are offered to meet the needs of customers and promote social performance over the whole service lifecycle (versus competitors) to survive in rival markets (Tseng et al., 2008). Therefore, social media has become a public channel for firms to disperse information. Customers enable the gathering of various and diverse types of information in terms of performance, operations, strategies and development from firms' official websites (Tseng, 2017). By pursuing long-term relationships (C16), firms strive to cooperate to develop products and processes through long-term relations with the partners in the supply chain. Supply chain partner development (C17) aims to develop a collaboration between manufacturers and suppliers within product development. Worker safety and human rights (C18) need to be practiced and to comply with governments' safety concerns and regulations regarding employment. Enhanced and more transparent communication (C19) brings visibility and effectiveness to SSCM. Innovation (C20) refers to the application of technology to promote efficiency by interpreting shared knowledge on buyer behaviors and social trends. Internal pressures (C21) are as the stresses and demands of a firm's employees. Social values and ethics (C22) assist in increasing collaboration success and ethical practices.

Operational risk consists of the risks that result from difficulties in balancing supply and demand (coming from the firm's usual operations) (Vahidi et al., 2018). To effectively preserve the environment, pollution control must be built into manufacturing technology to boost the integration of the supplier's operational processes and encourage stakeholders' learning and development (Wu et al., 2010; Tseng et al., 2008; Tseng et al., 2014). Tseng (2017) proposed a pattern of sustainability to present diverse features affecting internal and external attributes that serve all operational procedures. Demand and supply uncertainty (C23) might result from the unexpected or imprecise demand predictions, uncertainty is caused by the intense rivalries in the market, underused and overused capabilities or a lack of resilience. IT and information sharing risks (C24) refer to missing essential IT infrastructure and mechanisms to obtain and disseminate information instantaneously within the supply chain. A lack of sustainable knowledge/technology (C25) includes a lack of knowledge and understanding of sustainable technology, operations and approaches among partners. Lower responsiveness performance (C26) can be understood as the failure to reflect instantaneous demand (quantity, admixture and place) with its rational cost.

3. Method

This section presents the mathematical formulations to increase the understanding of the method and applications.

3.1. Transformation of the quantitative data

The diverse figures are characterized by different units in the proposed measures. These diverse figures with different units cannot make a comparison directly; they require gathering the crisp values in advance. All the crisp values need to be normalized to unit-free values with comparable features. The normalized values of Nc_{ij} can be found by employing Eq. (1) (Tseng, 2017; Tseng et al., 2015):

$$Nc_{ij} = \left(nc_{ij}^{N} - \min nc_{ij}^{N}\right) \Big/ \left(max\ nc_{ij}^{N} - \min nc_{ij}^{N}\right) X_{ij} \in (0,1); N = 1,2 \tag{1}$$

where $\max Nc_{ij}^{N} = max\{nc_{ij}^{1},\ nc_{ij}^{2}, \ldots nc_{ij}^{N}\}$; $\min Nc_{ij}^{N} = min\{nc_{ij}^{1}, nc_{ij}^{2}, \ldots\ldots nc_{ij}^{N}\}$.

3.2. Entropy weight method for social media

Sentences or paragraphs in web-text described as SSCM measures are arranged into three code groups, and these attributes are based on the pre-defined coding agenda. For example, the statement “supplier contributing effectively to a global partnership for sustainable development” was allocated to the code for supply chain partner development (C17) due to this proposed measure. This study analyzed the contrasting sample, then determined and improved the coding processes to enhance the reliability of the results. All analyzed actions were traced in a collateral Excel file to prevent repeat coding action. The obtained data were coded through a content analysis that enables the examination of the consistency of codes, independent of a firm's webpage (Braun and Clarke, 2006).

The social media frequency (f) is a value between 0 and 1 and is called the identification coefficient. Normally, this value is defined as 0.5.

$$\varepsilon_{0,i} = \sum_{\theta=1}^{\mu} w_{\theta} f_{0,i}(\theta) \ \ for\ i = 1, 2, \ldots.., \theta \tag{2}$$

The weightage of each characteristic term can be calculated by applying the entropy method satisfying $\sum_{\theta=1}^{\mu} w_{\theta}$. Entropy is an estimate of the decomposition of a system. The attribute of large entropy is adopted in this study because it has more diverse responses; accordingly, this attribute has a significant effect on the responses. The entropy method was adopted to determine the weightages of frequencies in terms of social media. Wen et al. (1998) used a mapping function $f_i : [0,1] \rightarrow [0,1]$ to define entropy through three conditions, where $f_i(0) = 0, f_i(x) = f_i(1-x)$ and $f_i(x)$ are monotonically increasing in the range of $x \in [0,\ 0.5]$. Therefore, the maximum value of this function exists when $x = 0.5$, and the value $e^{0.5}-1=0.6487$ ensures that the mapping result is within the range $[0,1]$. The following calculation procedures are employed to generate the entropy.

Summing the coefficients in all series for each term yields:

$$D_j=\sum_{i=1}^{\sigma}F_i\,(j) \tag{3}$$

Determining the entropy for each term yields

$$e_j=\pi\sum_{j=1}^{\sigma}w_e\left(\frac{F_i(j)}{D_j}\right) \tag{4}$$

Computing the entropy values yields

$$\mathrm{E}=\sum_{j=1}^{p}e_j \tag{5}$$

Weighting the terms yields

$$w_j=\frac{1/p-E(1-e_j)}{\sum_{j=1}^{p}1/p-E(1-e_j)}\ j=1,2,3\ldots..,p \tag{6}$$

The weightages of aspects allow computations through similar procedures and multiplication between the coefficient for social media and the corresponding term's weightage.

3.3. FSM-DEMATEL

FSM is used to solve the qualitative information. This method adopts a five-point linguistic scale, including Equal (E), Moderate (M), Strong (S), Demonstrably High (DH) and Extremely High (EH), to state the evaluation results. These scales must be transferred from qualitative values to quantitative values.

Supposing there is a series of criteria s under t numbers of aspects; u experts make the evaluations. Therefore, the aspects are obtained by employing exploratory factor analysis. Thus, these evaluations are denoted as a_{su}^t, where a represents the five-point linguistic scale. The scale must accumulate the weight frequencies to be converted into quantitative values, employing the following equation.

$$a_{su}^t=\left(v_s^t,w_s^t,x_s^t,y_s^t,z_s^t\right) \tag{7}$$

where $v_s^t,w_s^t,x_s^t,y_s^t,z_s^t$ present the accumulated frequencies from all experts for the scales.

However, these weighted frequencies need to be transformed into weightages by utilizing the equation below.

$$a_s^t=\left(\frac{v_s^t}{u},\frac{w_s^t}{u},\frac{x_s^t}{u},\frac{y_s^t}{u},\frac{z_s^t}{u}\right) \tag{8}$$

These weightages acquire the crisp value cp_s^t.

$$cp_s^t=1\times\frac{v_s^t}{u}+2\times\frac{w_s^t}{u}+3\times\frac{x_s^t}{u}+4\times\frac{y_s^t}{u}+5\times\frac{z_s^t}{u} \tag{9}$$

To measure the overall performance, this study adopts a geometric mean to compute the measurement criticality (MC_s), which presents how criteria are related to the following equation:

$$MC_s=\sqrt[t]{\prod_{t=1}^{k}cp_s^t},\ t=1,2,\cdots,k \tag{10}$$

Furthermore, the factor weightages must be attained using the following equation:

$$aw_s^t=cp_s^t\Big/\sum_{t=1}^{k}cp_s^t \tag{11}$$

These factor weightages are integrated with the original weighted frequencies a_s^t to generate a membership function for the aspects.

$$G^t=aw_{s\otimes as}=\left(aw_s^t\right)_{n\times k}\otimes\left(a_s^t\right)_{k\times v}=\left(aw_s^t a_s^t\right)_{n\times v}=\left(g_{\delta\tau}^t\right)_{n\times v} \tag{12}$$

therefore, $g_{\delta\tau}$ can be rewritten as $(g_{\delta\tau}^{1t},g_{\delta\tau}^{2t},g_{\delta\tau}^{3t},g_{\delta\tau}^{4t},g_{\delta\tau}^{5t})$.

Subsequently, utilizing the equation below gives the value of the membership function.

$$\tilde{g}_{\delta\tau}^t=1\times g_{\delta\tau}^{1t}+2\times g_{\delta\tau}^{2t}+3\times g_{\delta\tau}^{3t}+4\times g_{\delta\tau}^{4t}+5\times g_{\delta\tau}^{5t} \tag{13}$$

Thus, the overall weightages ($O_{\delta\tau}^t$) can be obtained using the following equation.

$$O_{\delta\tau}^t=\tilde{g}_{\delta\tau}^{t\otimes aw_s^t}=\left(\tilde{g}_{\delta\tau}^t\right)_{\rho\times n\otimes\left(g_{\delta\tau}^t\right)_{n\times v}}=\left(ow_{\delta\tau}^t\right)_{\rho\times v} \tag{14}$$

where $ow_{\delta\tau}^t$ can present as $(ow_{\delta\tau}^{1t},ow_{\delta\tau}^{2t},ow_{\delta\tau}^{3t},ow_{\delta\tau}^{4t},ow_{\delta\tau}^{5t})$.

The following equations can assist in determining the overall performance (PM^o).

$$pr_\varphi^t=ow_{\delta\tau}^{1t}+ow_{\delta\tau}^{2t}+ow_{\delta\tau}^{3t}+ow_{\delta\tau}^{4t}+ow_{\delta\tau}^{5t} \tag{15}$$

$$PM^o=\sqrt[t]{\prod_{\varphi=1}^{\gamma}pr_\varphi^t} \tag{16}$$

Moreover, these crisp values have to be arranged into self-matrix M by utilizing the following equation.

$$M=\left[m_{bc}^t\right]_{s\times s}=\left[cp_s^{t\otimes w_{j\otimes Nc_{ij}}}\right]_{n\times n},n=1,2,\cdots,s \tag{17}$$

Using the arithmetic mean aggregates the self-matrices under certain aspects to attain the direct relation matrix D via the equation below.

$$D=\sum_{b=1}^{t}m_{bc}^t/t=[m_{bc}]_{s\times s} \tag{18}$$

Next, the normalized direct relation matrix D can be generated by utilizing the following equation:

$$\overline{D}=m_{bc}\Big/\max_{1\le b\le s}\sum_{b=1}^{s}m_b \tag{19}$$

Implementing the equation below gives the total relation matrix (E).

$$E=\overline{D}\left(\forall-\overline{D}\right)^{-1}=\left[e_{\alpha\beta}\right]_{s\times s} \tag{20}$$

Therefore, $\forall$ is the unit matrix.

Calculating the driving (q) and dependent (r) factors by applying the following equations gives the cause and effect diagram.

$$\begin{cases} q = \left(\sum_{\alpha=1}^{s} e_{\alpha\beta}\right)_{s\times 1} = (e_\alpha)_{s\times 1} \\ r = \left(\sum_{\beta=1}^{s} e_{\alpha\beta}\right)_{1\times s} = \left(e_\beta\right)_{1\times s} \end{cases} \tag{21}$$

Utilizing the coordinates $(q+r, q-r)$ maps the criteria onto the causal diagram. If $(q-r)>0$, the criteria are categorized into a cause group; otherwise, the criteria are in an effect group. $(q+r)$ expresses the importance of the criteria where criteria located on the right-hand side have a higher importance. Moreover, $(q+r, q-r)$ can divide the diagram into four quadrants. The criteria that fall into the first quadrant are driving factors; the second quadrant has voluntary factors; the third quadrant has independent factors; and the core problems are located in the fourth quadrant.

3.4. Proposed analytical steps

1. The proposed measures are collected from the literature, and the EFA is applied to test the validity and reliability.
2. The quantitative data must be transformed into a unit-free and comparable scale using Eq. (1). For social media, the frequencies must be counted using Eqs. (2)–(6) to acquire crisp values.
3. The qualitative information and hierarchical structure are found using the FSM-DEMATEL and the accumulated weight frequencies are found using Eq. (7). These weight frequencies are transferred into weights using Eq. (8).
4. Eq. (9) is used to gather the crisp values. Then, these crisp values can generate measurement criticality with Eq. (10). Eqs. 11–16 are adopted to determine the overall performance of the aspects.
5. In addition, the crisp values of the criteria need to be arranged into individual self-matrices using Eq. (17). Then, the self-matrices are integrated to attain the direct relation matrix in Eq. (18).
6. Eqs. (19) and (20) are used to generate the total relation matrix. Then, Eq. (21) determines the driving and dependent factors, and taking $(q+r)$ and $(q-r)$ as horizontal and vertical axes creates the causal diagram.

4. Results

This section includes the industrial background and the analytical results from the proposed steps.

4.1. Industrial background

The Taiwanese textile industry is located mostly in the Asia Pacific region. This study collected information from Cambodia, China, Indonesia, Philippines, Vietnam and Taiwan. The respondents are Taiwanese-owned textile manufacturing firms. The manufacturers provide excellent service in the green market, as the firms continuously pursue the reduction of environmental impacts, the improvement of social responsivity, the increase in economic benefits and the development of green products and services to comply with the requirements of the supply chain networks. Taiwanese textile firms remain at the forefront of green practices by maintaining forceful performance in finance and meeting social responsibility requirements. Hence, the firms often require a series of reliable attributes to balance the economic, environmental and social considerations within the decision-making process.

Thus, qualitative, quantitative and social media data should be used in the decision-making process. The firms' managers were enthusiastic about understanding how big data might provide different insights into data-driven SSCM performance. Firms in the industry usually apply qualitative information and quantitative data in their decision-making. These two data approaches might be rare in recent decision-making processes, however, because social media is progressively becoming a reference. Hence, this study proposes the social media approach and integrates these data as big data in different structures. Therefore, this study compares the qualitative information and quantitative data in the analytical results. The analysis is discussed in the following section, which provides detailed results and comparisons.

4.2. Analytical results

This section follows the proposed analytical steps to determine the data-driven SSCM performance in a hierarchical structure assessment.

1. Table 3 presents the EFA, which examined whether the criteria produce the expected aspects. Factor analysis with principal components was used. A criterion from the proposed measures had a low factor loading of 0.453 and was removed because the retained criteria all had loadings greater than 0.6 (Hair et al., 1998). This study computed Cronbach's alpha for each aspect. The Cronbach's alpha was greater than 0.7 for all aspects, indicating reliability and convergent validity (Bagozzi and Yi, 1988). Tables 1 and 2
2. Quantitative data must be transformed to a unit-free and comparable scale using Eq. (1). Social media should count the frequencies using Eqs. (2)–(6) to acquire crisp values. Tables 4 and 5 present the defuzzification results and rankings of aspects and criteria.
3. Table 5 presents the 4 aspects of membership functions, which explain 68.7% of the variance. The FSM-DEMATEL computes the accumulating weight frequencies in Eq. (7). These weight frequencies are transformed into weights using Eq. (8).
4. Eq. (9) is used to determine the crisp values. These crisp values are arranged into individual self-matrices using Eq. (10). Then, the self-matrices are integrated into the direct relation matrix using Eq. (11). The total relation matrix is presented in Table 6, using Eqs. (12) and (13) to generate the total relation matrix. Eq. (14) enables the driving and dependent factors to be determined, and taking $(q+r)$ and $(q-r)$ as horizontal and vertical axes produces the causal diagram, as shown in Table 7.
5. (see Table 8).Fig. 1 indicates that there are 11 driving criteria: economic stability (C2), logistics optimization (C3), corporate strategy and commitment (C4), logistical integration (C5), technological integration (C7), environment awareness training (C12), green warehousing (C14), green product design (C15), SC partner development (C17), worker safety and human rights (C18) and lower responsiveness performance (C26).

5. Implications

This section reinforces the theoretical basis of SSCM and offers significant managerial implications.

5.1. Theoretical implications

This study contributes to the literature by exploring decisive attributes and offers better insights on dealing with SSCM issues. The results of this study deliver evidence suggesting that social development (As3) and economic benefit (As1) are the decisive attributes of SSCM. Consequently, these two attributes must be considered as prerequisites for improving supply chain

Table 1
Proposed measures.

Criteria		References
C1	Strategic supplier collaboration	Dubey et al. (2017a,b); Mathivathanan et al. (2018); Seuring et al. (2008); Tseng (2017)
C2	Economic stability	
C3	Logistics optimization	
C4	Corporate strategy and commitment	
C5	Logistical integration	
C6	Joint development	
C7	Technological integration	
C8	Reverse logistics, using product recovery techniques	Dubey et al. (2017a,b); Ivascu et al. (2015)
C9	Collaborating with suppliers	
C10	Green packaging	
C11	Effective use of by-products	
C12	Environment awareness training	
C13	Environment conservation	
C14	Green warehousing	
C15	Green product design	
C16	Long term relationships	Dubey et al. (2017a,b); Mathivathanan et al. (2018); Tseng et al. (2014)
C17	SC partner development	
C18	Worker safety and human rights	
C19	Enhanced communication	
C20	Innovation	
C21	Internal pressures	
C22	Social values & ethics	
C23	Demand and supply uncertainty	Song (2017); Tseng (2013); Tseng et al. (2018b); Zailani et al. (2012)
C24	Information technology and information sharing risks	
C25	Lack of sustainable knowledge/technology	
C26	Lower responsiveness performance	

Table 2
Linguistic preferences and the scale.

Linguistic preferences (Important degree)	Five-Points Lingustic Scale
Extreme High	*EH*
Demonstrated High	*DH*
Strong	*S*
Moderate	*M*
Equal	*E*

management. The detailed discussions are addressed below.

Social development continues to attract firms' attention in the management domain. The following discussion offers significant insights that can assist decision makers in assessing the technological fitness of big data in the field of SSCM and its dramatic social impact on firms' role in managing the supply chain to obtain resilient and practical strategies and action schemes (Roβmann et al., 2017). Big data analysis is essential to promoting the understanding of social development conditions for the public and private sectors. Converting data into useful information and knowledge clarifies the crucial issues, simplifies the problems and

Table 3
Exploratory factor analysis.

Aspects	Criteria		Factor Loadings
Economics benefits (As1) (Cronbach's alpha: 0.87, AVE: 0.79)	C1	Strategic supplier collaboration	0.915
	C2	Economic stability	0.907
	C3	Logistics optimization	0.905
	C4	Corporate strategy & commitment	0.893
	C5	Logistical integration	0.875
	C6	Joint development	0.868
	C7	Technological integration	0.854
Environment impacts (As2) (Cronbach's alpha: 0.87, AVE: 0.83)	C8	Reverse logistics, using product recovery techniques	0.873
	C9	Collaborating with suppliers	0.865
	C10	Green packaging	0.862
	C11	Effective use of by-products	0.855
	C12	Environment awareness training	0.845
	C13	Environment conservation	0.827
	C14	Green warehousing	0.808
	C15	Green product design	0.795
Social development (As3) (Cronbach's alpha: 0.87, AVE: 0.77)	C16	Long term relationships	0.855
	C17	SC partner development	0.843
	C18	Worker safety and human rights	0.821
	C19	Enhanced communication	0.801
	C20	Innovation	0.793
	C21	Internal pressures	0.785
	C22	Social values & ethics	0.777
Operational risks (As4) (Cronbach's alpha: 0.78, AVE: 0.77)	C23	Demand and supply uncertainty	0.789
	C24	Information technology and information sharing risks	0.764
	C25	Lack of sustainable knowledge/technology	0.752
	C26	Lower responsiveness performance	0.709

Table 4
Defuzzification and criteria ranking.

	E	*M*	*S*	*DH*	*EH*	cp_s^{As1}	cp_s^{As2}	cp_s^{As3}	cp_s^{As4}	MC_s	Ranking
C1	0.115	0.115	0.346	0.154	0.269	3.346	2.808	2.731	2.923	8.5518	13
C2	0.346	0.346	0.231	0.038	0.038	2.077	3.462	3.154	2.615	7.5580	19
C3	0.269	0.115	0.154	0.231	0.231	3.038	2.538	2.923	2.808	7.5152	20
C4	0.160	0.240	0.320	0.120	0.160	2.880	2.692	2.808	2.808	7.2568	24
C5	0.154	0.231	0.154	0.231	0.231	3.154	3.385	3.077	2.962	10.9483	4
C6	0.231	0.115	0.077	0.308	0.269	3.269	2.808	3.423	3.192	10.4735	5
C7	0.240	0.000	0.240	0.320	0.200	3.240	2.692	2.692	3.462	7.8284	15
C8	0.240	0.200	0.080	0.160	0.320	3.120	3.385	3.346	2.654	11.7785	3
C9	0.080	0.160	0.520	0.160	0.080	3.000	3.346	2.615	2.923	8.7515	12
C10	0.120	0.280	0.280	0.040	0.280	3.080	3.000	2.615	3.423	8.0554	14
C11	0.240	0.280	0.200	0.160	0.120	2.640	2.846	3.115	3.269	7.8028	16
C12	0.120	0.160	0.320	0.040	0.360	3.360	2.692	3.000	3.308	9.0462	11
C13	0.160	0.160	0.240	0.320	0.120	3.080	2.731	3.231	3.038	9.0578	10
C14	0.120	0.120	0.360	0.360	0.040	3.080	3.077	2.923	3.077	9.2339	8
C15	0.160	0.360	0.160	0.200	0.120	2.760	3.077	2.538	2.808	7.1858	25
C16	0.192	0.077	0.308	0.192	0.231	3.192	3.385	3.308	3.115	11.9129	2
C17	0.038	0.115	0.154	0.231	0.462	3.962	2.923	2.692	2.462	10.3922	6
C18	0.115	0.115	0.385	0.308	0.077	3.115	2.731	2.692	2.615	7.6348	18
C19	0.080	0.240	0.120	0.400	0.160	3.320	2.885	2.885	3.038	9.2086	9
C20	0.308	0.115	0.231	0.077	0.269	2.885	3.115	3.154	2.923	9.6995	7
C21	0.115	0.308	0.154	0.308	0.115	3.000	2.269	3.154	3.462	7.1568	26
C22	0.115	0.154	0.308	0.231	0.192	3.231	2.269	3.154	3.462	7.7073	17
C23	0.115	0.192	0.269	0.308	0.115	3.115	2.269	3.154	3.462	7.4321	21
C24	0.077	0.346	0.115	0.346	0.115	3.077	2.269	3.154	3.462	7.3403	22
C25	0.038	0.115	0.154	0.231	0.462	3.962	3.077	2.923	2.808	11.9921	1
C26	0.160	0.160	0.240	0.320	0.120	3.080	2.731	2.615	3.115	7.3325	23

Table 5
Defuzzification and aspect ranking.

	E	*M*	*S*	*DH*	*EH*	cp^{As1}	cp^{As2}	cp^{As3}	cp^{As4}	MC^t	Ranking
As1	0.115	0.269	0.192	0.308	0.115	3.038	3.192	3.077	3.038	9.948	2
As2	0.192	0.231	0.115	0.269	0.192	3.038	3.346	2.846	2.962	9.646	3
As3	0.077	0.115	0.346	0.308	0.154	3.346	3.000	3.115	3.000	10.425	1
As4	0.269	0.269	0.077	0.231	0.154	2.731	3.192	3.269	3.231	9.500	4

promote the exploration of solutions to benefit the community. Firms must develop and discuss social issues, characterize and forecast vital study and humanitarian organizations, and create more inclusive and extensive social systems and solutions to privacy issues and data risks.

Economics benefits have turned out to be progressively strategic considerations for ventures of all sizes. There are numerous advantages that the firm can obtain by utilizing cleaner creation techniques. First, the adoption of big data can generate huge potential benefits in predicting changes to economy and society. Big data analysis has been demonstrated to promote the forecasting of economic indicators regarding unemployment levels (Vicente et al., 2015), assist managers to discover market trends so that they can foresee opportunities, and support policy makers in rapidly and more accurately monitoring the influences of a broader range of policies and public grants (Blazquez and Domenech, 2017). Additionally, the basis for the steady operation of the firm is economic steadiness in the current market. If a firm can remain economically steady, it has more advantages than other firms in the same field in terms of loans, investments, staff and suppliers (Mokeev et al., 2015). Moreover, logistics has a noteworthy effect on the environment, as reusing materials can diminish the negative impacts on the earth (Turrisi et al., 2013).

5.2. Managerial implications

This study indicates implications for firms that achieve progress in SSCM performance. SSCM performance is a basic foundation to build competitive advantage. Although prior studies have shown the variety in SSCM measures, this variety did not appear to have a particularly clear linkage. Eleven criteria have the most driving and dependent factors: economic stability (C2), logistics optimization (C3), corporate strategy and commitment (C4), logistical integration (C5), technological integration (C7), environment awareness training (C12), green warehousing (C14), green product design (C15), SC partner development (C17), worker safety and human rights (C18) and lower responsiveness performance (C26). In addition, five criteria involve the importance of fundamental attributes to drive SSCM performance. Thus, to attain better SSCM performance, management needs to pay attention to operational activities.

Corporate strategy and commitment (C4) is a strategic-level policy and synchronization with the strategic team at the tactical and operational levels in the firm; it is essential for the introduction and practice of sustainable development. Lacking a corporate strategy and management involvement hampered firms' sustainability efforts. SSCM strategic alignment is important for sustainable development, and the collected information might drive firm performance. This study emphasizes the role of commitment, particularly from the top management, which precedes supply chain partners in pursuing sustainability practices. The relationship between commitment and sustainable practices is critically important for firms. Still, technological integration (C7) enhances sustainability performance (Mathivathanan et al., 2018) and is the first priority in terms of social aspects. Firms actively move from their initiatives toward SSCM to acquire competitive advantages over rivals. Although conformity with imperative actions, such as certifications and laws stipulated by the government and human

Table 6
FSM-membership functions and overall performance for aspects.

	As1						As2						As3						As4					
	$\tilde{g}_{\delta\tau}^{As1}$	Membership Function					$\tilde{g}_{\delta\tau}^{As2}$	Membership Function					$\tilde{g}_{\delta\tau}^{As3}$	Membership Function					$\tilde{g}_{\delta\tau}^{As4}$	Membership Function				
As1	3.055	0.210	0.155	0.216	0.210	0.209	2.951	0.200	0.239	0.149	0.233	0.179	2.992	0.203	0.203	0.189	0.208	0.197	2.990	0.203	0.203	0.189	0.208	0.197
As2	3.029	0.153	0.211	0.272	0.179	0.185	3.039	0.190	0.197	0.205	0.199	0.208	2.951	0.194	0.247	0.168	0.196	0.195	3.082	0.194	0.247	0.168	0.196	0.195
As3	3.255	0.132	0.190	0.202	0.241	0.234	2.849	0.225	0.210	0.201	0.218	0.146	4.047	0.236	0.156	0.244	0.322	0.295	3.053	0.236	0.156	0.244	0.322	0.295
As4	3.327	0.103	0.233	0.156	0.252	0.257	2.631	0.271	0.231	0.211	0.169	0.117	2.978	0.256	0.121	0.196	0.241	0.185	3.235	0.256	0.121	0.196	0.241	0.185
Total Performance ($\boldsymbol{PM^o}$)			**8.98**	**68.7%**																				

Table 7
Total relation matrix (E).

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25	C26
C1	3.019	2.865	3.106	2.962	2.933	2.942	2.962	2.779	2.769	2.846	2.952	3.077	2.99	2.962	3.077	3.087	2.904	3.288	3.135	3.048	3.038	3.029	3.125	3.135	3.125	3.106
C2	2.989	3.154	3.055	2.942	3.060	3.322	2.971	2.990	3.173	2.933	3.266	2.955	3.144	3.146	3.065	2.852	3.164	2.845	3.188	3.010	2.769	3.346	2.884	2.980	3.212	2.829
C3	3.212	3.045	2.630	3.200	3.023	2.939	2.986	2.971	3.192	3.183	2.952	3.184	3.088	3.183	2.963	2.971	3.312	3.202	2.958	3.059	3.047	3.349	2.952	3.026	2.968	2.998
C4	3.050	3.090	3.282	3.181	3.005	3.142	3.214	2.967	2.916	2.925	3.135	3.096	3.019	3.012	3.019	3.113	3.125	2.923	2.884	3.155	2.938	3.077	3.019	3.058	3.152	3.181
C5	3.263	3.052	2.923	3.16	3.138	3.218	3.168	3.002	2.997	2.930	3.000	2.971	3.128	3.080	3.351	3.221	3.210	3.005	3.162	3.173	3.135	2.761	3.109	3.012	3.240	2.962
C6	3.173	3.056	2.926	2.923	3.067	2.673	3.000	3.093	3.139	3.000	2.916	3.058	3.067	3.105	3.084	2.968	3.235	3.000	3.029	2.885	3.031	2.962	2.875	3.026	3.057	3.097
C7	3.067	2.942	3.178	2.832	3.060	3.075	2.969	3.205	3.101	2.913	3.019	2.972	3.212	2.931	3.019	2.922	3.080	3.162	2.897	3.087	3.072	2.904	2.917	3.145	3.144	2.940
C8	3.056	3.032	2.962	2.785	2.941	3.010	3.048	2.990	2.990	3.064	2.952	3.021	2.721	3.111	2.728	2.933	2.885	3.174	3.183	3.117	3.058	2.739	3.407	3.148	3.237	2.971
C9	3.127	3.194	3.031	3.034	3.028	2.943	2.984	2.981	2.875	3.173	2.901	3.164	2.844	3.001	2.940	2.778	3.049	2.810	3.117	3.148	3.029	3.177	2.863	3.096	3.183	3.000
C10	3.096	2.899	3.080	3.019	2.958	3.066	2.933	3.085	2.910	3.129	2.673	3.007	3.07	3.075	2.977	3.058	2.793	3.039	3.001	2.842	3.065	2.894	2.830	3.067	2.911	2.902
C11	3.166	3.118	2.911	2.989	3.027	2.865	2.985	2.913	3.067	3.242	3.106	2.740	3.072	2.900	3.192	3.022	2.892	2.798	2.933	3.010	2.654	3.077	2.865	3.078	2.845	2.933
C12	3.018	2.983	3.078	2.837	2.971	3.121	3.090	2.942	3.144	3.159	3.288	2.715	3.123	2.949	3.308	3.154	2.885	3.088	3.212	2.942	3.154	2.824	3.192	3.175	2.931	3.222
C13	3.042	2.748	2.864	2.947	2.682	2.952	3.029	3.205	2.962	3.013	3.078	3.232	3.346	3.022	2.777	2.740	2.951	3.302	3.067	3.243	3.127	3.004	3.008	3.010	3.133	3.071
C14	3.154	3.031	2.823	3.040	3.174	2.846	3.221	2.783	3.264	3.215	3.087	3.126	3.174	3.076	3.058	2.815	3.058	3.192	2.990	2.893	3.026	3.365	2.972	3.030	2.952	3.127
C15	3.037	2.976	2.723	3.029	3.202	3.312	3.050	3.292	3.057	3.082	2.939	3.237	3.106	2.88	3.087	3.024	3.063	2.962	2.785	3.104	3.267	2.977	3.040	3.221	3.240	2.948
C16	2.968	2.948	2.919	3.265	2.895	3.282	3.117	3.245	2.864	3.212	2.933	3.141	3.067	3.184	3.06	2.957	3.205	2.832	2.838	3.029	2.998	3.128	2.805	3.030	3.186	2.805
C17	2.913	2.963	3.341	2.944	2.822	2.989	3.052	3.115	3.250	3.019	3.222	2.902	3.010	2.963	3.076	3.010	2.861	3.106	2.963	2.993	3.039	2.989	3.098	3.049	3.339	3.037
C18	3.196	3.135	3.010	3.260	2.897	3.110	3.022	3.382	3.031	3.010	2.968	3.046	3.020	3.009	3.183	3.083	2.833	3.067	3.173	3.117	3.087	3.187	2.849	3.011	2.963	3.019
C19	2.970	3.078	2.798	2.952	3.140	3.080	2.846	3.077	3.187	2.872	2.980	2.825	2.788	3.202	3.01	3.041	3.115	3.038	2.932	3.165	2.826	3.021	2.922	3.183	3.165	2.981
C20	2.846	2.837	3.059	2.624	3.147	3.021	3.118	2.887	3.168	3.048	3.070	3.220	2.852	2.940	3.059	3.115	3.163	3.183	2.943	2.942	3.177	2.938	3.135	3.051	3.115	3.036
C21	2.989	2.983	3.023	2.936	3.048	2.825	3.106	3.195	3.163	3.112	2.885	2.700	3.167	3.087	3.029	2.873	3.08	3.087	3.000	2.890	3.137	2.827	3.01	3.125	3.010	3.215
C22	2.736	3.293	2.704	2.904	3.019	3.000	2.953	2.904	3.195	3.029	2.914	2.875	2.982	3.058	3.084	3.059	2.993	3.225	3.075	3.375	2.722	3.099	3.106	2.949	3.254	3.126
C23	3.221	3.129	3.134	2.882	3.163	3.000	2.948	3.021	3.010	3.174	2.925	3.142	3.125	3.202	3.274	2.858	3.033	3.009	2.999	2.806	2.885	2.904	2.969	3.163	2.980	2.748
C24	3.221	2.931	3.002	3.224	3.018	3.015	2.970	3.125	3.057	3.276	2.846	3.144	3.010	3.160	2.798	2.796	2.799	3.321	2.923	3.011	2.983	2.803	2.986	2.985	2.938	3.001
C25	2.538	2.972	3.264	3.088	2.993	2.923	3.144	2.803	2.947	2.704	3.113	2.827	2.920	2.933	3.042	2.951	3.037	3.139	3.038	2.990	3.048	3.037	3.087	3.143	2.788	2.930
C26	3.212	3.056	3.176	3.183	2.761	3.135	2.966	2.952	3.048	3.023	3.163	3.009	3.000	3.172	3.030	3.072	3.03	2.826	3.001	3.115	3.362	3.127	3.150	2.856	3.269	3.001

Table 8
Driving and dependence powers.

	(q)	(r)	$(q+r)$	$(q-r)$
C1	41.202	41.562	82.764	(0.360)
C2	41.716	41.154	82.870	0.561
C3	41.903	40.903	82.806	1.001
C4	41.955	40.970	82.924	0.985
C5	42.324	40.981	83.305	1.343
C6	41.307	41.315	82.622	(0.008)
C7	41.470	41.347	82.818	0.123
C8	41.195	41.371	82.565	(0.176)
C9	41.311	41.667	82.979	(0.356)
C10	40.744	41.561	82.305	(0.817)
C11	40.747	41.048	81.795	(0.301)
C12	41.854	41.099	82.953	0.756
C13	41.353	41.441	82.795	(0.088)
C14	41.851	41.590	83.441	0.261
C15	41.927	41.568	83.494	0.359
C16	41.546	40.621	82.168	0.925
C17	41.620	41.290	82.910	0.330
C18	41.948	41.747	83.695	0.201
C19	41.167	41.123	82.290	0.044
C20	41.433	41.495	82.928	(0.062)
C21	41.333	41.262	82.594	0.071
C22	39.862	41.185	81.047	(1.323)
C23	39.964	40.988	80.952	(1.023)
C24	39.777	41.818	81.594	(2.041)
C25	40.752	42.118	82.870	(1.366)
C26	41.955	40.996	82.952	0.959

rights, offers the incentive to adopt SSCM practices, internal practices stipulated by the management are the eventual driver of change. Fulfilling the TBL approach and considering the supply chain factors around entire decision-making aspects played a vital part in affecting other practices. Therefore, these compelling practices are the prerequisites to making other practices successful.

In addition, economic stability (C2) indicates that modern firms with sustainable supply chains have better performance than firms that relied on their traditional supply chains during the economic crisis. Hence, economic steadiness is a critical driver (Dubey et al., 2017a,b), as higher economic steadiness can generate more autonomy given unanticipated changes in market situations and can reduce the risk of bankruptcy. In this study, the analysis of firms' economic steadiness includes a model for economically steady situations. Consequently, indicators of firms' economic steadiness should be analyzed by firm leaders, who then need to predict the firm's activities according to the economic steadiness model and make administrative decisions to promote a firm's sustainable development. In particular, environmental awareness training (C12) requires firms to infuse the concept of sustainable environmental practices into management, employees and the community (Ivascu et al., 2015), from enhancing the utilization of natural resources and discouraging land development to launching broader environmental campaigns. This finding clearly indicates that humans thoroughly rely on the endurance of the natural environment. This training is seen as a requirement to develop the firm's processes and achieve the firm's objectives.

Logistics optimization (C3) stresses the need to possess energy-efficient logistics and an effective supply chain system to attain better sustainability and decrease the global carbon footprint. This study highlights the need to develop a reverse logistics network, resource utilization, and product reuse and recycling practices and include corporate social responsibility and sustainability issues into reverse logistics. The results indicate that logistics optimization is incorporated to understand SSCM practice. Hence, logistics optimization is a decisive driver of SSCM performance. In addition, logistical integration (C5) includes the relationships that a firm has with the supplier networks and that includes logistics support integration as a central element of supply chain management. The network purchases the raw materials, converts them into diverse types of goods, causing finished goods to be delivered to customers through the distribution system. Managing this network requires the professional knowledge and ability to optimize the logistics to offer a certain volume of a specific item at a specific time and price.

Green warehousing (C14) includes issues related to the use of green energy sources and strategies. A warehouse management system is important for sustainability performance, and it is necessary to have recycling facilities. The warehouses in supply chains generate a great deal of packaging waste. The adoption of certified reusable containers is a solution to lower costs and reduce waste. Thus, warehouses should strive to maximize the usage of storage space, minimize the cost of storage and reduce energy consumption. Develop warehouse sustainability is significant and has become a critical topic for future studies of sustainability that not only address green warehouses and related issues on the

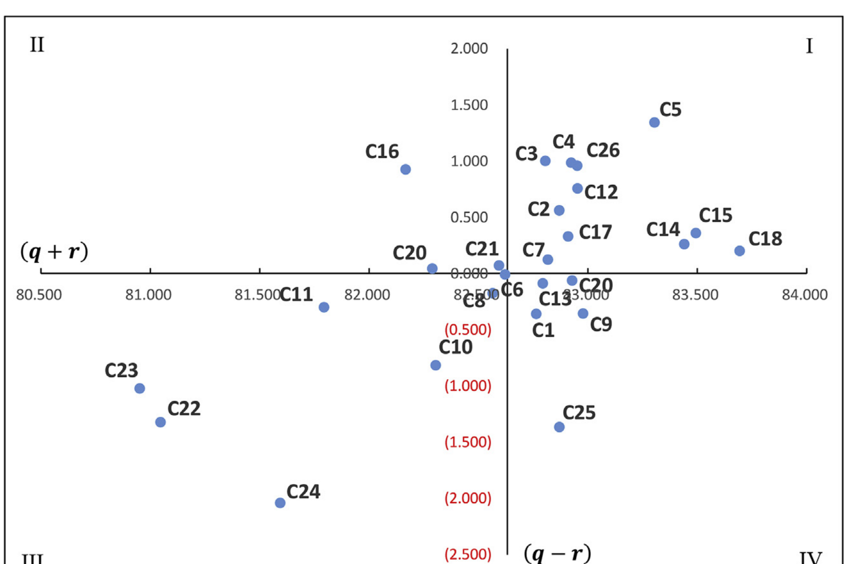

Fig. 1. Driving and dependence powers.

utilization of green energy and strategies but also improve energy efficient technology. Thus, green product design (C15) offers a path to deal with environmental issues by designing and innovating products (Dubey et al., 2017a,b). Green design positively affects firms' performance and has a significant influence on sustainable development. This study shows that green product design might generate either conflict or agreement between economic and environmental goals based on the structure and contracts of the supply chain, while only an appropriate contract design can resolve this conflict and balance economic and environmental benefits.

Supply chain partner development (C17) is cooperation between suppliers and manufacturers in product development and links multiple partners in a network in the product development process. There are major benefits of partnership, such as increased market share, improved service and quality and shorter product development. To promote the supplier's service quality, the service firm needs to establish good relations with its main suppliers by attempting to develop a partnership program. This step is needed to focus the firm's stakeholders, such as employees, solicitors, clients, and local community, on sustainable development. Firms and their suppliers can create highly competitive supply chain networks. Worker safety and human rights (C18) need to take first priority to align with the safety considerations and government regulations in terms of employment (Mathivathanan et al., 2018). The firm's goal should be to create value while emphasizing the high standards for human rights performance. Workers have a right to a safe and healthy workplace and work. This result reveals that management and government stakeholders might prioritize economic benefits rather than human rights. Providing a safe environment and promoting human rights should allow a firm to achieve long-term success.

Lower responsiveness performance (C26) is an operational risk factor. Greater supply chain risk leads to poorer performance metrics, such as flexibility and responsiveness. This study attempted to analyze these risk attributes using a methodology to reduce the impact on SSCM performance. The attributes are also the basis on which to identify and evaluate alternatives to improve business processes (Avelar-Sosa et al., 2014). Each stakeholder in the supply chain should aim to reach common goals, such as customer satisfaction and enhanced competitiveness in sustainability. Hence, firms, suppliers and customers should discuss how to address the measurement and SSCM performance improvement. These criteria are related to SSCM performance, which helps firms to compete with their competitors in the market. Hence, managers should try to make use of the advantages in these criteria and develop them properly so that firms can attain long-term SSCM development on their own.

6. Concluding remarks

The proposed method is a practical and helpful approach to rank, screen and compare the alternatives through measurement. The FSM-DEMATEL is mathematical method to transfer the interrelationships between cause and effect criteria in a visual structure model. The proposed aspects and criteria have been ranked, with 4 main aspects and 26 criteria. The findings indicate that social development and operational risk are decisive aspects of SSCM performance, which implies that these aspects have the potential to improve SSCM performance. In detail, social development was found to be the basis of leverage and to facilitate economic benefits, environment impacts and operational risks, which could enhance financial performance. In the textile industry, due to its complex supply chain, applying social development to supply chain practices offers several benefits. Social development in supply chain management can create synergy in development. Economic benefits help to save costs, such as transactional costs and communication costs; quickly respond to market changes; enhance coordination; and facilitate collaboration between supply chain partners. The diversified operational risk in the supply chain can pass to the firm through collaboration, helping the firm to rapidly respond to market changes and customer needs.

The contributions of this study are identifying the decisive SSCM performance attributes in the textile industry and examining the interrelationship among the attributes by utilizing big data to explain data-driven SSCM performance. Big data was found to possess great potential for promoting SSCM performance in terms of impact, economic benefits, operational risk and social development. Additional, in a gradual and integrative way, big data are a basic attribute to improve SSCM performance, drive the environmental impact criteria, and control the firm's economic benefits, operational risk and social development activities related to firm performance. However, in a highly competitive environment, the market is becoming increasingly global and competition is therefore becoming more intense. Efforts to achieve and promote efficiency and effectiveness of big data are critical for firms to retain their competitive advantages. The action scheme for the industry can also assist firms in rivaling their competitors. Overall, the insights obtained from this study offer a rigid foundation for further study.

This study nevertheless has several limitations. First, this study examined the existing SSCM literature to explore the interrelationships among related aspects and criteria; accordingly, the aspects and criteria studied may not be extensive. Second, the sample is concentrated in the Taiwanese textile industry only. Therefore, the external generalizability of the findings is constrained. Future studies should use the data in multiple industries to overcome the possible generalizability issues. Likewise, a sample of experts in different industries could be considered in order to benefit from a comparison of the effective aspects and criteria. Moreover, to enhance the accuracy of the analysis of SSCM, it is necessary to uncover and include more potential attributes of big data.

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