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Original citation & hyperlink:
Wu, K-J, Liao, C-J, Tseng, M-L, Lim, M, Hu, J & Tan, K 2017, 'Toward Sustainability: Using Big Data to Explore Decisive Supply Chain Risk Factors Under Uncertainty' Journal of Cleaner Production, vol 142, no. 2, pp. 663-676
https://dx.doi.org/10.1016/j.jclepro.2016.04.040

DOI 10.1016/j.jclepro.2016.04.040
ISSN 0959-6526
ESSN 1879-1786

Publisher: Elsevier

Toward Sustainability: Using Big Data to Explore Decisive Attributes of Supply Chain Risks and Uncertainties

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Abstract

Supply chain risks and uncertainties exist in the Taiwanese light-emitting diode industry due to rapid market changes aimed at sustainability. The risks and uncertainties caused by the social media data, quantitative data and qualitative data (referred to herein as big data) which industry unable to handle these booming information to respond customer needs. As result of these various data have their own characteristics that affect decision making regarding to develop firms' capabilities. This study proposes to use fuzzy and grey Delphi methods to identify a set of reliable attributes, and then transforming big data into comparable scale for considering the impacts. Subsequently, applying fuzzy and grey Decision Making Trial and Evaluation Laboratory determine the causal relationship for supply chain risks and uncertainties. Accordingly, this study aggregates the various data for undertaking an extensive investigation of supply chain risks and uncertainties. The results reveal that capacity and operation have greater influence than do other factors and that risks stemming from triggering events are difficult to diagnose and control. The implications and conclusions of these findings are addressed herein.

Keywords: big data, supply chain risks and uncertainties, sustainability indicators, Decision Making Trial and Evaluation Laboratory (DEMATEL), Delphi method

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1. Introduction

Social media has become an essential channel for firms to spread information, thus customers are able to acquire enormous amounts of diversified information from firms' official websites and through their performances and developments. This phenomenon forces Taiwanese light-emitting diode (LED) firms to realize social media information and develop related capabilities to comply with customer and stakeholder expectations toward sustainability. However, it might generate the supply chain risks and uncertainties (SCRU) while developing the capacities. In order to mitigate the SCRU and ensure the development efficiently, several studies proposed sustainability indicators to assist firms in arriving the sustainability (Erol et al., 2011; Hauer, 2003; Linton et al., 2007; Rahdari & Anvary Rostamy, 2015; Veleva et al., 2001). Moreover, firms lack appropriate methods for making decisions regarding the development of proper capabilities (Hauer, 2003; Speier et al., 2011). More specifically, various information, such as quantitative data regarding operations, qualitative data from management and social media information (big data), is involved to the firms' decision-making process. Hence, to assist firms in diagnosing SCRU with sustainable development perspective, there is an essential need to identify, assess and analyze these diverse data sources (Hallikas et al., 2004; Peck, 2005; Sodhi et al., 2012).

In the literature, Chopra and Sodhi (2004) stress that managing SCRU is difficult because the individual risks are often interconnected with actions that mitigate some risks while exacerbating others. The collaboration theory is used to enhance the understanding of SCRU and explores the decisive attributes for monitoring the risks in these interconnected relationships. Furthermore, Lozano (2007) emphasizes that collaboration is a key problem-solving attribute that facilitates dynamic interactions and that incremental actions produce enduring significant improvements toward sustainability. Jiang et al. (2009) stress that supply chain problems are a timely and important managerial topic as such problems impact costs, operations, risks and uncertainties. In addition, risks associated with disruption, production and complexity result in the erosion of brand equity and the loss of consumer confidence, both of which impact on financial performance (Kleindorfer et al., 2003; Speier et al., 2011). Heckmann et al. (2015) categorizes risks into controllability, organization and operations. In conclusion, these prior studies provide a foundation which can develop a comprehensive framework and assessment in diagnosing SCRU.

Particularly, prior studies felt the need in capturing the risks due to the incremental complexity and uncertainties exist in supply chain, thereby making actions harder or even impossible to predict (Helbing et al., 2006). Nonetheless various risks in daily operations, such as an unanticipated decrease in demand or a sudden boom in growth, remain, and few firms have taken the commensurate actions that allow supply chains to confront the risks from these abrupt events (Sodhi, 2005; Sodhi et al., 2012; Nooraie & Mellat Parast, 2015). Confronting these risks requires a framework with a quantitative assessment to detect potential SCRU that is applicable to both practitioners and researchers (Ghadge et al., 2012; Tang & Nurmava Musa, 2011). Hence, this study attempts to aggregate various data, including quantitative data from operations, qualitative data from management and social media data, to facilitate decision making and provide comprehensive consideration to mitigate the risks toward sustainability. Subsequently, the fuzzy Delphi method (FDM) and the grey Delphi method (GDM) are proposed to screen unnecessary SCRU measures and to compare the abilities of the fuzzy Decision Making Trial and Evaluation Laboratory (FDEMATEL) and the grey Decision Making Trial and Evaluation Laboratory (GDEMATEL) to address uncertainties and risks in the supply chain. The advantage of comparing these methods is to enhance the accuracy in making decision.

Thus, the objective of this study is to develop an assessment that supports firms in exploring the decisive attributes and enhancing the understanding of SCRU by aggregating from big data and different data types. This assessment allows managers to make decisions in a logical, systematic, precise and comprehensive manner based on cross-functional considerations. Consequently, the results reveal the decisive SCRU attributes to be used as a guide by firms to efficiently distribute their resources. The remainder of this study is composed of six sections. The next section presents an extensive literature review and includes a discussion of SCRU, collaboration theory and sustainability indictors. The gaps and proposed measures are addressed in section 3, and a detailed discussion of methods is provided in section 4. Section 5 provides the empirical results of the evaluation, section 6 discusses theoretical and managerial implications, and a summary of the discussions, implications, contributions, limitations, future research and conclusions are included in the last section.

2. Literature Review

Brief discussions of SCRU, collaboration theory and sustainability indicators are offered to enhance the understanding of these specific terms.

2.1. Supply Chain Risks and Uncertainties

Due to the increasing complexity and interrelation of modern supply chains, the type and nature of uncertain developments and the effect of specific actions are becoming harder to forecast or even becoming unpredictable (Helbing et al., 2006). Several studies categorize the risks into triggering events and functional risks, both of which synonymously refer to SCRU. Triggering events are often understood as the starting point for risk identification to reduce uncertainties (Klinke & Renn, 2002). Functional risks, refer to the occurrence of a sudden problem within a firm’s basic operational functions. For instance, Peck (2006) defines SCRU as anything that disrupts or impedes information, material or product flow from the original supplier through to the delivery of the final product to the ultimate end user. Though prior studies have addressed multiple SCRU aspects, a reliable theoretical model is still lacking (Heckmann et al., 2015; Speier et al., 2011; Zsidisin, 2003).

Firms often focus on consistent but low impact risks rather than on high impact less probable risks. Furthermore, firms also encounter difficulties addressing SCRU due to the interconnected relations among individual risks (Chopra & Sodhi, 2004; Trkman & Mccormack, 2009). This study captures multiple aspects from a comprehensive literature review to increase the validity, and it further categorizes these aspects into two groups: functional risks and triggering events. Functional risks include problems stemming from capacity, operations, products and organization, whereas triggering events represent risks caused by disruption, costs, complexity, controllability and reputation (Chopra & Sodhi, 2004; Heckmann et al., 2015; Jiang, 2009; Ratnasingam, 2006; Speier et al., 2011; Tang, 2006).

There are increasing evidences to discover the negative impacts from SCRU, though many firms lack the capability to assess potential impacts on their supply chain because they underinvested in developing the sustainability to respond to the risks (Hauer, 2003). Thus, to diagnose potential SCRU, firms must extend even further by adopting sustainability indicators (Speier et al., 2011). Although most firms apply standard financial indicators to track financial risks, some non-financial risk should be taken to monitor and demonstrate chronological change (Chen et al. 2014; GRI, 2011). Hence, firms must be aware that the indicators shall precisely reflect performance and provide appropriate guidelines for determining risks and uncertainties (Heckmann et al., 2015; Rahdari & Anvary Rostamy, 2015).

2.2. Collaboration Theory

Collaboration involves engaging in an interactive process to decide on related issues of a particular domain (Lozano, 2007; Wood & Grey, 1991). As such, it is considered a path toward sustainability due to its changes in individual actions to participate in concerted efforts and to attain common interests (Lozano, 2008). In addition, supply chain partners strengthen mutual benefits and share mutual risks (Powell et al., 1996; Soosay et al., 2008). Hence, collaboration reduces internal conflict and creates a common goal by developing values and a sustainability vision to eliminate potential SCRU e.g., lack of controllability, loss of capacity and increase in costs (Lozano, 2007; Van Hoof & Thiell, 2014). Therefore, to develop a theoretical basis for SCRU, the concepts of congruence and alignment must be implemented.

With respect to congruence, the discussion focuses on the degree of consistency in internalizing sustainability, in other words, the spreading of the impacts of sustainability to other aspects (Myers, 2004; Nadler & Tushman, 1980). However, the definition of congruence in the field of SCRU refers to the probabilities of event occurrence, thus suggesting that risks might generate limitations for the supply chain (Heckmann et al., 2015). In addition, Lozano (2008) proposes the concept of alignment to express a type of need/objective that is consistent across different levels to avoid misunderstandings and conflicts. Similarly, the illustration of alignment in the SCRU field denotes a need/objective to prevent unintentional and intentional actions (Speier et al., 2011). These two concepts deliver a clear picture that firms can use to realize how potential risks may exist in developing sustainability.

The theoretical framework of SCRU is based on the collaboration theory wherein the inter-relations of each risk are addressed through the following concepts. SCRU can be categorized into concepts of congruence and alignment. Capacity, operation, product and organization belong to the congruence category and represent the basic functions of firms that may suffer from either unintentional or intentional activities that result in risks. Disruption, costs, complexity, controllability and reputation are grouped into the category of alignment. These triggering events are considered points of risk identification (Heckmann et al., 2015; Klinke & Renn, 2002). When SCRU increase, a commensurate investment in developing sustainability may prevent the materialization of these risks and uncertainties. Hence, SCRU must be linked with sustainability indicators to explore the decisive attributes necessary for effective commensurate investments.

2.3. Sustainability Indicators

The Brundtland Commission Report (1987), the Earth Summit (1992) and Ranganathan (1998) define sustainability indicators as *"the information used to measure and motivate progress toward sustainable goals"*. Although the use of these indicators has become a standard procedure for all ranks of government, non-government organizations and firms when developing firm capabilities (Milman & Short, 2008), most firms apply certain aspects and sets of attributes from only a single sustainability indicator. However, there are many sustainability assessments with different sets of indicators from other methods of aggregation (Rahdari & Anvary Rostamy, 2015). This study demonstrates the essentials of aggregating the necessary proposed and evaluated indicators in a real case scenario.

However, aggregation is an extremely complicated decision-making process, and therefore, the mathematical consistency involved in aggregation must be addressed (Romero & Linares, 2014). Nonetheless, once firms overcome this mathematical problem, sustainability indicators can be a barometer of the socio-economic conditions to use for monitoring the various aspects of overall risk (Liu, 2014). In addition, the potential risks and opportunities that firms may encounter in the long term to screen through the application of sustainability indicators provide a better alternative for managing opportunities and risks (Rahdari & Anvary Rostamy, 2015). These attributes support the premise of this study, that is, firms develop the capability to mitigate the emergence of SCRU by launching sustainability indicators.

This study adopts FDM and GDM to filter the aggregated indicators and explores the decisive attributes by applying the FDEMATEL and the GDEMATEL to assist firms in concentrating their resources to prevent the occurrence of risks under uncertainty. In previous studies, most practitioners have questioned the need to aggregate and have experienced difficulties in obtaining mathematical consistency. Therefore, though quite complex, it is necessary to distinguish conditions from pressures, identify causal relationships and measure firm risk (Milman & Short, 2008). Accordingly, sustainability indicators can be used as an evaluative tool to supporting firms in diagnosing risks and reducing the complexities.

3. Rationale of study

Gaps in previous studies are examined for the purpose of enhancing the validity and contributions of this study, and the proposed measures for the study are presented herein

3.1. The study gaps

Ratnasingam (2006) conducted in-depth multiple case comparisons to discover potential attributes of SCRU. To complete the theoretical basis and create a unifying decision-making framework, Ellis et al. (2011) reviews 79 studies and then proposes an interdisciplinary framework that offered new insights into the risk decision-making process. However, these prior studies neglect the inter-relations among attributes. To this end, Speier et al. (2011) adopts a MANOVA for a correlation analysis and reveals a significant interrelation between complexity and product risk. Tazelaar and Snijders (2013) apply a conjoint analysis with 255 respondents to identify how problems are ultimately resolved after a transaction. Atwater et al. (2014) extends this conjoint analysis by associating it with a statistical method to develop a scoring model for SCRU; however, uncertainty remained. To reduce uncertainty, Heckmann et al. (2015) conducts a review of definitions, measurement methods and models, and then reveals the missing attributes in the prevailing definitions, quantification measures and modeling approaches.

It is important to offer an assessment that includes mathematical consistency in aggregating big data to gather precise and reliable evaluations from selected sustainability indicators as doing so allows firms to establish the related capabilities necessary to respond to SCRU and represents the capability to link responses and performances to sustainability. However, most indicators address a single dimension, and only a few indicator assessments enable reflection on the situation. Moreover, even fewer indicators possess the ability to link with the system and express the resulting state (Briassoulis, 2001). Though previous studies have proposed several types of sustainability indicators, the critical point is to aggregate the components necessary for truly assessing the condition while simultaneously maintaining mathematical consistency (Böhringer & Jochem, 2007; Milman & Short, 2008; Rahdari & Anvary Rostamy, 2015). Romero and Linares (2014) emphasize the essential aggregation of indicators to solve complicated decision-making problems.

Sustainability is required to use various data for realizing the available resources (Wong & Zhou, 2015). Hence, Belaud et al. (2014) apply scientific simulation based on big data and collaborative work to develop sustainability in natural hazards management. Nativi et al. (2015) discover and assess the challenges based on the big data concept. Though the big data concept increases the reliability of attribute evaluation, the attributes must still be limited for firms to concentrate their resources and investments. In reality, it is impossible to implement all attributes as available resources and investments are restricted. Hence, this study proposes FDM and GDM to eliminate unnecessary attributes based on the opinions of several experts. Subsequently, the FDEMATEL and GDEMATEL are used to classify the remaining attributes into cause and effect groups and to map the relationships among the attributes, thus ensuring reliable results that can guide firms in managing SCRU.

3.2. Proposed Measures

Chopra and Sodhi (2004) stress that though the disruption of material flow anywhere in the supply chain is unpredictable and rare, it is also quite damaging when it does occur. Disruption often affects supply chain performance, thereby harming all supply chain partners

(Zsidisin et al., 2005). The occurrence of disruption in the supply chain, which may be the result of a man-made or natural disaster (Chen et al., 2012), has a long term negative impact on the firm's financial performance (Tang, 2006). To prevent the supply chain from collapsing, the proposed sustainability indicators, which include preventing biodiversity loss, reducing air emissions, preserving natural resources and conserving energy (Azapagic, 2004; Chen et al., 2014; Marnika et al., 2015; Rahdari & Anvary Rostamy, 2015), can mitigate disruption.

Capacity, unlike inventory, can be developed in manufacturing and can be grown or reduced over a period of time. Although building excess capacity often becomes a strategic consideration, it is not always a perfect solution for preventing risk (Chopra & Sodhi, 2004). Normally, excess capability causes a financial burden when the firm addresses the occurrence of risky events. Hence, monitoring capacity using sustainability indicators is an effective technique for preventing risks. The sustainability indicators include capacity building, ensuring availability for long-term prevention, implementing an available dispute resolution mechanism, ensuring capital efficiency and improving margins (Reed et al., 2006; Milman & Short, 2008; Choi & Sirakaya, 2006; Samul et al., 2013).

Some studies concentrate on the relationship between labor-related costs and risks and find that rising labor costs significantly decrease margins (Jiang et al., 2009; Roberts, 2006). Thus, to prevent cost risks, this study proposes using three sustainability indicators as triggers to observe the variations in costs: employee education and skill development, the creation of employment and employee work conditions (Azapagic, 2004; Chen et al., 2014; Jiang, 2009). However, firms also encounter cost risks when research and development activities are launched (Onat & Bayer, 2010). In particular, when sustainable product design is being developed, many resources and investments are required to explore new technologies to overcome current issues (Bask & Kuula, 2011; Chiu & Chiu, 2012; Rahdari & Anvary Rostamy, 2015).

Operational risks are related to supply chain coordination, which might result in insufficient procedures, ineffective persons and inefficient short-systems (Bhattacharyya et al., 2010; Lockamy & McCormack, 2009). However, practitioners have found it difficult to identify the difference between risks due to disruption and operational risks. The major difference between these two risks is the degree of control (Byrne, 2007). For example, disruption is an event that is under less control, and once it occurs, it results in major damage. On the contrary, operational risks are due to either the intentional or unintentional actions or goals and thus are more controlled (Chen et al., 2012). In other words, operational risks can be prevented by implementing or addressing the appropriate sustainability indicators, such as land use and rehabilitation, labor relations, compliance with supply chain partners, water use and effluents, and leachates and resource use and availability (Chen et al. 2014; de Araujo & de Oliveria, 2012; Dues et al., 2013; Jiang et al., 2009; Linke et al., 2013; Marnika et al., 2015).

Firms suffer from damage to their reputations in media-rich societies stemming from criticism from non-governmental organizations and fair trade/no sweat organizations (Jiang et al., 2009). This negative publicity easily and rapidly spreads through social media, thereby causing harm to brands and resulting in a significant loss in the market share. This is, in part, because firms have insufficient resources to check different types of social media. This study provides sustainability indicators that firms use to assess the probability of reputational risk, such as local economic impacts, health and safety factors, social investments, global warming effects and environmental impacts (Chen et al., 2014; Esteves et al., 2012; Marnika et al., 2015; Rahdari & Anvary Rostamy, 2015).

As products are considered risky in terms of their product nature and supply chain or intentional interruptions (Speier et al., 2011), preventative measures focus on improving process management and reducing environmental impact. Moreover, there are measures to mitigate product risk, e.g., decreasing the use of hazardous materials, reducing solid waste, applying life cycle assessment and increasing product stewardship (Chen et al., 2014; Marnika et al., 2015; Samuel et al., 2013). In addition, a supply chain features intricate and sometimes counterintuitive interactions among its elements, thus resulting in complexity. The complexity of the supply chain is an aggregate measure of the structure, type and volume of its interdependent activities, transactions and processes (Manuj & Mentzer, 2008). As such, these activities also generate information, constraints and uncertainties that increase risk. Therefore, to help firms mitigate the risk from complexity, this study selects four sustainability indicators: security, corruption, policy coherence and relationships with the local community (Blancas et al., 2011; Chen et al., 2014; Samuel et al., 2013).

Controllability refers to the ability to manage and limit the frequency and impact of risk (Heckmann et al., 2015) and is therefore highly dependent on the firm’s environment and its objectives. Controllability is concerned with reducing risks associated with the environment, supply, internal cooperation processes, internal controls and demand. The indicators are intended to avoid the risks due to controllability by enhancing crisis management, environmental regulations and wealth distribution. (Esquer-Peralta, 2007; Rahdari & Anvary Rostamy, 2015; Samuel et al., 2013). The risks to the organization require the involvement of top management and a commitment of resources and finances (Ratnasingam, 2006). The sustainability indicators assist in developing an organizational structure and process to ensure long-term sustainability and reduce the probability of risk (Choi & Sirakaya, 2006). To mitigate risks within the organization requires strong information exchange, process integration, operational linkages and internal cooperation. Thus, the indicators to avoid organization risks include the use of traditional rights and knowledge, management efficiency, community outreach and environmental education (Ou & Liu, 2010; Rahdari & Anvary Rostamy, 2015; Samuel et al., 2013).

4. Method

This section aggregates qualitative data, social media data and quantitative data. In addition, FDM, GDM, FDEMATEL and GDEMATEL are used to enhance the accuracy of decision-making and the reliability of the study. Additionally, the proposed analytic procedures are presented.

4.1. Data Gathering

Qualitative Data

The proposed measures are intended to enhance the validity of the study. The original set of measures includes nine aspects and 38 attributes related to the Taiwanese LED industry. The ability of FDM and GDM to eliminate unnecessary aspects and attributes is then discussed. The collected information in obtained from practitioners, a group that includes professors, CEOs, vice presidents, managers and engineers, all of whom have experience in the industry. The results of the assessment are presented in Table 1, in which seven aspects and 16 attributes are identified.

Table 1. The Results of Experts' Assessment

Aspects (Risks)		Attributes (SI)	
AS1	Capacities	C1	Available capacity for long-term prevention of shortages
		C2	Capital efficiency
		C3	Margin improvement
AS2	Cost	C4	Employee education and skills development
AS3	Operations	C5	Labor relations
		C6	Compliance with supply chain partners
		C7	Resource use and availability
AS4	Reputation	C8	Health and safety
		C9	Global warming and environmental impacts

AS5	Products	C10	Reduction of solid waste
		C11	Application of life cycle assessment
		C12	Increased product stewardship
AS6	Controllability	C13	Crisis management
		C14	Environmental regulations
AS7	Organization	C15	Management efficiency
		C16	Environmental education

Social Media

Firms use social media to communicate with external parties using a multipronged strategy that crosses various platforms (Piskorski, 2011). Web-based information is a platform that allows firms to deliver messages, information and performances to the public. This study uses Nvivo 10 software to capture fragment terms and frequencies from several LED firms' websites, such as Everlight Electronics Co., Ltd., Epistar Corporation, Edison Opto Corporation, etc. Content analysis establishes the existence and frequency of attributes (Chan et al., 2015). However, the feature of these accumulated frequencies from social media is grey relational grade. Hence, these grey relational grades must be transferred into comparable weights to evaluate their effects (Delgado & Romero, 2016).

Entropy presents the degree of disorganization of a system. The larger the entropy value, the greater the diversity of information. In this study, entropy weight identifies the effects of social media frequency. Assume there are n terms and the accumulated frequency is denoted as $f_i, i = 1,2,3,\cdots,n$. In the first step, value f_i is normalized by the following equation:

$$f_i' = f_i / \sum_{i=1}^{n} f_i \quad (1)$$

Second, the entropy f_i^h of each term is computed using the following equation:

$$f_i^h = -(ln(n))^{-1} \sum_{i=1}^{n} f_i' \, ln(f_i') \quad (2)$$

Third, the degree of divergence for the intrinsic information is obtained using the following equation:

$$f_i^{div} = 1 - f_i^h \quad (3)$$

Finally, to acquire the entropy weight f_i^e for each term, the following equation is applied:

$$f_i^e = f_i^{div} / \sum_{i-1}^{n} f_i^{div} \quad (4)$$

Quantitative Data

Big data require extensive management capabilities characterized by volume, velocity and variety (Laney, 2001). In other words, big data contain several data sets, strict constraints and heterogeneity (Nativi et al., 2015). This study obtains data from financial statements as well as daily operational information which include input and output raw materials, production time, number of defective units over the past decade. These data are characterized by various units and are unable to be compared directly (Lin et al., 2014). Therefore, a data transformation is performed to attain comparable values.

$$a'_{ij} = a^y_{ij} - min\, a^y_{ij} / max\, a^y_{ij} - min\, a^y_{ij}, \quad a'_{ij} \in [0,1];\ i = 1,2,\cdots,n; j = 1,2,\cdots,k; y = 1,2,\cdots 10 \tag{5}$$

where $min\, a^y_{ij} = min(a^1_{11}, a^1_{12}, \cdots a^{10}_{ij})$ and $max\, a^y_{ij} = max(a^1_{11}, a^1_{12}, \cdots a^{10}_{ij})$.

Then, relevant investments for n^{th} terms of all aggregated firms is assessed as follows:

$$a^n_{ij} = \sum_{j=1}^{k} a'_{ij} / y \times k \tag{6}$$

4.2. FDM

Decision making in an uncertain environment is related to subjective judgments that are vague and imprecise (Tseng, 2009). Hence, fuzzy set proposed to overcome the imprecision. In addition, this study used FDM as an initial filter to find the proper aspects and attributes. This hybrid method increases the quality and efficiency of the response time and feedback (Chen et al., 2014; Noorderhaben, 1995).

Assume that S is a universe of discourse that states $S = \{s_1, s_2, \cdots, s_n\}$. The fuzzy set A of S is denoted as a set of ordered pairs $\{(s_1, f_A(s_1)), (s_2, f_A(s_2)), \cdots, (s_n, f_A(s_n))\}$, where $f_A(S)$ is the 0 to 1 membership function of A. The value of $f_A(s_i)$, $i = 1,2,\cdots n$ presents the degree of membership of s_i in A (Chang et al, 2011; Tseng, 2009). The membership function is used in the following equation to express triangular fuzzy numbers (TFNs) $\bar{\delta} = (\delta_l, \delta_m, \delta_r)$:

$$f_A(s_i) = \begin{cases} 0, s_i < \delta_l \\ \frac{s_i - \delta_l}{\delta_m - \delta_l}, \delta_m \geq s_i \geq \delta_l \\ \frac{\delta_r - s_i}{\delta_r - \delta_m}, \delta_r \geq s_i \geq \delta_m \\ 0, s_i > \delta_m \end{cases} \tag{7}$$

Triangular fuzzy numbers rely on a three-value assessment that contains the minimal value δ_l, the mean value δ_m and the maximal value δ_r. Attribute values must be in accordance with the linguistic scales to be converted into triangular fuzzy numbers. Table 2 shows the corresponding triangular fuzzy numbers with the linguistic scales as proposed by Wu et al. (2015). Suppose k experts evaluate a significant ℓth element $\bar{\delta} = (a_{k\ell}, b_{k\ell}, c_{k\ell})$, where $k = 1,2,3,\cdots,m$ and $\ell = 1,2,3,\cdots,n$. The weight of $\bar{\delta}_\ell$ for the ℓth element is $\bar{\delta}_\ell =$

(a_ℓ, b_ℓ, c_ℓ), for which $\alpha_\ell = \min(a_{k\ell}), b_\ell = \left(\frac{\sum_1^n \beta_{ab}}{n}\right)$, and $c_\ell = \max(c_{k\ell})$. The α-cut approach is used to obtain the convex combination value for S_ℓ, as in the equations below:

$$\begin{gathered} L_\ell = a_\ell - \alpha(b_\ell - a_\ell) \\ U_\ell = c_\ell - \alpha(c_\ell - b_\ell) \\ S_\ell = \int(U_\ell, L_\ell) = \lambda[U_\ell + (1-\lambda)L_\ell] \end{gathered} \tag{8}$$

Normally, α adopts 0.5 to present the general condition. If the experts are optimistic adopters, the value of α can be set to 1; on the contrary, 0 is the conservative choice. Therefore, λ is the degree of optimism of the decision maker. This value used to balance the extreme opinions of experts. The definite value S_ℓ can then be generated. Finally, $\mu_{FDM} = \sum_{\ell=1}^{n} S_\ell / n$ is the threshold for screening acceptable attributes using the following equation:

$$\begin{gathered} If\ S_\ell \geq \mu_{FDM}, \text{the } \ell\text{th attribute is accepted as a potential evaluating attribute;} \\ If\ S_\ell < \mu_{FDM}, \text{the attribute is rejected} \end{gathered} \tag{9}$$

Table 2. Linguistic Scales for Corresponding TFNs

Scales	Linguistic Preferences	Corresponding Triangular Fuzzy Numbers
1	No influence/importance	(0, 0.1, 0.3)
2	Very low influence/importance	(0.1, 0.3, 0.5)
3	Low influence/importance	(0.3, 0.5, 0.7)
4	High influence/importance	(0.5, 0.7, 0.9)
5	Very high influence/importance	(0.7, 0.9, 1.0)

4.3. GDM

Grey theory is a mathematical theory proposed by Deng (1982) that stems from the grey set. This efficient approach addresses problems with uncertainty and discrete data (Tseng, 2009). The assessment values for conversion into the corresponding grey numbers are presented in Table 3.

Table 3. Linguistic Scales for corresponding grey numbers

Scales	Linguistic Preferences	Corresponding Grey Numbers (ΔG)
1	No influence/importance	(0, 0.3)
2	Very low influence/importance	(0.3, 0.5)
3	Low influence/importance	(0.3, 0.7)
4	High influence/importance	(0.5, 0.9)

5	Very high influence/importance	(0.7, 1.0)

The grey numbers are presented. Hence, the grey number ΔG is presented as an interval value $\Delta G = [G^{\ell}, G^{u}]$ such that $\Delta G = [-\infty, G^{u}]$ and $\Delta G = [G^{\ell}, \infty]$ represent the lower-limit and upper-limit grey numbers, respectively, both of which are then defined as uncertain information (Bhattacharyya, 2015).

$$\begin{array}{c} If\ G^{\ell} \to -\infty\ and\ G^{u} \to \infty, \Delta G\ is\ a\ black\ number, \\ which\ means\ that\ there\ is\ not\ any\ meaningful\ information. \\ If\ G^{\ell} = G^{u}, \Delta G\ is\ considered\ to\ be\ white\ number, \\ which\ means\ that\ complete\ information\ is\ gathered. \\ Otherwise, \Delta G = [G^{\ell}, G^{u}]\ is\ a\ grey\ number \\ and\ contains\ insufficient\ and\ uncertain\ information \end{array} \tag{10}$$

Assume that there are k experts in the evaluating group. The assessments of attribute relations ΔG_n can be obtained as follows:

$$\Delta G_n^k = (\Delta G_v^1 + \Delta G_v^2 + \cdots + \Delta G_v^k)/k$$

(11)

where $\Delta G_n^k, n = 1,2,\cdots,v$ is the attribute relation given by the kth expert and is expressed as $\Delta G_n^k = [G_n^{\ell k}, G_n^{u k}]$. The completed information $\bar{\bar{\Delta}} G_n^k$ is gathered from the following equation, where $\bar{\bar{\Delta}}$ represents the equal-weight mean whitenization value of the grey parameter (Memon et al., 2015):

$$\bar{\bar{\Delta}} G_n^k = \left(G_n^{\ell k} + G_n^{u k}\right)/2$$

(12)

Thus, $\mu_{GDM} = \sum_1^n \bar{\bar{\Delta}} G_n^k / n, n = 1,2,\cdots,v$ is the threshold for screening suitable attributes using the following equations:

$$\begin{array}{c} If\ \bar{\bar{\Delta}} G_n^k \geq \mu_{GDM}, \text{the } n\text{th attribute is accepted as a potential evaluation attribute;} \\ if\ \bar{\bar{\Delta}} G_n^k < \mu_{GDM}, \text{the attribute is rejected.} \end{array} \tag{13}$$

4.4. FDEMATEL

After the screening process, the resulting acceptable attributes rely on the FDEMATEL to identify their causal relationships. This approach enables a display of the visual analysis through a visual diagram. Hence, the FDEMATEL has been applied to assist in solving complicated system problems in various fields (Tseng, 2011; Wu et al., 2015). Assume that initially there are sets of attributes $S = \{S_i | i = 1,2,\cdots n\}$ and pairwise inter-relations. The linguistic scale is then implemented into the evaluation assessment, as displayed in Table 2.

Suppose that there are k respondents and the linguistic scale must be transferred to triangular fuzzy numbers $\bar{\delta}_{xy} = \left(\delta_{xy}^{lk}, \delta_{xy}^{mk}, \delta_{xy}^{rk}\right)$, which represents the degree to which attribute x affects attribute y in the kth response. The defuzzification process requires triangular fuzzy numbers be converted into crisp values (Lin, 2013). This study adopted Max-Min to normalize the triangular fuzzy numbers before obtaining the completed crisp values. The Max-Min normalization process follows the equation below:

$$\begin{aligned} \tau\delta_{xy}^{lk} &= \left(\delta_{xy}^{lk} - \min \delta_{xy}^{lk}\right)/\Delta_{min}^{max} \\ \tau\delta_{xy}^{mk} &= \left(\delta_{xy}^{mk} - \min \delta_{xy}^{lk}\right)/\Delta_{min}^{max}, where\ \Delta_{min}^{max} = \max \delta_{xy}^{rk} - \min \delta_{xy}^{lk} \\ \tau\delta_{xy}^{rk} &= \left(\delta_{xy}^{rk} - \min \delta_{xy}^{lk}\right)/\Delta_{min}^{max} \end{aligned} \tag{14}$$

Identifying the left (l) and right (r) normalized value, we have the following:

$$\begin{aligned} \tau l_{xy}^{k} &= \tau\delta_{xy}^{mk}/\left(1 + \tau\delta_{xy}^{mk} - \tau\delta_{xy}^{lk}\right) \\ \tau r_{xy}^{k} &= \tau\delta_{xy}^{rk}/\left(1 + \tau\delta_{xy}^{rk} - \tau\delta_{xy}^{mk}\right) \end{aligned} \tag{15}$$

Then, gathering the total normalized crisp values (τ_{xy}^{k}):

$$\tau_{xy}^{k} = \left[\tau l_{xy}^{k} \times \left(1 - \tau l_{xy}^{k}\right) + \left(\tau r_{xy}^{k}\right)^{2}\right]/\left[1 - \tau r_{xy}^{k} + \tau r_{xy}^{k}\right] \tag{16}$$

Attaining the crisp values:

$$c_{xy}^{k} = \min \delta_{xy}^{lk} + \tau_{xy}^{k} \times \Delta_{min}^{max} \tag{18}$$

The final step of the transformation is to aggregate the crisp values:

$$c_{xy} = \sum_{1}^{k} \tau_{xy}^{k}/k \tag{19}$$

To arrange these crisp values in a pairwise comparison and express them as a direct relation matrix $S_{n\times n}^{d}$, the matrix can be rewritten as $S^{d} = \left[c_{xy}\right]_{n\times n}$. Subsequently, the direct matrix S^{d} must be normalized into S^{n}, and the normalized matrix S^{n} can be obtained from the following equation:

$$S^{n} = \forall \times S^{d},\ \text{where}\ \forall = 1/\max_{1\le x\le n} \sum_{y=1}^{n} c_{xy}, x, y = 1,2,\cdots,n \tag{20}$$

Once the normalized matrix S^{n} is obtained, it must be correlated with the identity matrix to obtain the total relation matrix S^{t}, as in the following computation:

$$S^{t} = S^{n} \times (D - S^{n})^{-1}, \text{where D is the identity matrix} \tag{21}$$

Finally, the sums of the rows and columns in the total relation matrix are used to acquire the vectors v and h, respectively. The computation of vectors is obtained using the following equations:

$$\begin{aligned} S^{t} &= \left[c_{xy}^{t}\right]_{n\times n}, x, y = 1,2,\cdots,n \\ v &= \left[\sum_{x=1}^{n} c_{xy}^{t}\right]_{n\times 1} = \left[c_{x}^{t}\right]_{n\times 1} \\ h &= \left[\sum_{y=1}^{n} c_{xy}^{t}\right]_{1\times n} = \left[c_{y}^{t}\right]_{1\times n} \end{aligned} \tag{22}$$

Thus, the causal diagram is produced. The vertical axis, $(v - h)$, represents the role of the attribute. If $(v - h)$ is negative, the attribute is considered to be the effect, whereas if

$(v-h)$ is positive, the attribute is considered to be the cause. Subsequently, $(v+h)$ is the horizontal axis and represents the importance of the attributes.

4.5. GDEMATEL

The acceptable attributes $C=(C_1,C_2,\cdots C_n)$ form a pairwise comparison to evaluate the relationship among them. This evaluation is denoted by response p that is required to convert the linguistic scale into a grey number $\Delta G=[G^{\ell},G^{u}]$, which is presented in Table 3. These grey numbers consist of a direct relation grey matrix $G^p, p=1,2,\cdots,n$, which is expressed as follows:

$$G^p=\begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_n \end{array}\begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} [0,0] & G_{12}^p & \cdots & G_{1n}^p \\ G_{21}^p & [0,0] & \cdots & G_{2n}^p \\ \vdots & \vdots & \ddots & \vdots \\ G_{n1}^p & G_{n2}^p & \cdots & [0,0] \end{bmatrix} \end{array} \tag{23}$$

where G_{xy}^p is the grey number for the degree of influence of x on y in the p response.

Using the average to aggregate the response, the computation process is as follows:

$$G^d=\left(\sum_{i=1}^{p} G^p/p\right) \tag{24}$$

Accordingly, the aggregated direct relation grey matrix G is normalized into a direct relation matrix G^n as follows:

$$G^n=G^d\Big/\max_{1\le x\le n}\sum_{y=1}^{n} G_{xy} \tag{25}$$

The normalized direct relation matrix G^n is then incorporated in the total relation matrix G^t as follows:

$$G^t=G^n(I-G^n)^{-1},\ \text{where I is the identity matrix} \tag{26}$$

Subsequently, v and h are denoted by $n\times 1$ and $1\times n$ vectors, respectively, and represent the sum of the rows and the columns in the total relation matrix G^t, respectively. Thus, v_x represents the sum of the xth row within matrix G^t, which contains both the direct and indirect effects from attribute x on other attributes, and h_y represents the sum of the yth column in matrix G^t and represents the effects received by attribute y from other attributes. The computation is as follows:

$$\begin{aligned} v_x&=\sum_{x=1}^{n} G_{xy}\forall x \\ h_y&=\sum_{x=1}^{n} G_{xy}\forall y \end{aligned} \tag{27}$$

where $x=y$, $(v+h)$ states the degree of importance for the attribute and $(v-h)$ presents the degree of causality. A causal diagram is then drawn for decision-making such that $[(v_x+h_y),(v_x-h_y)],\forall\, x=y$.

4.6. Proposed Analytic Procedures

The proposed analytic procedures are divided into three sub-sections, as presented in Figure 1.

Figure 1. Analytic Procedures

Experts' Assessment Stage:

1. The proposed SCRU measures reflect a realistic industry situation to eliminate unnecessary measures through FDM and GDM. The eliminating procedures are based on

Eqs. (7-9) and (18-21), respectively, and the final results are presented in Table 1.

2. The remaining aspects must be incorporated to evaluate the interactions by applying the FDEMATEL and GDEMATEL, as done in Eqs. (10-17) and (22-26), respectively. The aspects are then arranged to create a visual two-dimensional map.

Big Data Acquisition and Transformation stage:

1. The content analysis reveals the terms related to the listed measures and to the accumulated frequencies obtained from social media data. In addition, the quantitative data are derived from firms' financial statements and daily operations.
2. The frequency (social media) is transformed into entropy weight by using Eqs. (1-4) and the relevant data are converted into comparable values using Eqs. (5-6).

Data Aggregation and Result Comparison stage:

1. The aggregated entropy weights and quantitative transformations are incorporated into the decision-making matrix to compare the results of the FDMATEL and GDEMATEL using Eqs. (10-17) and (22-26), respectively. Subsequently, the causal diagram is generated based on the vertical $(v-h)$ and horizontal $(v+h)$ axes and the mapping of the attributes into the diagram.
2. The interactions are identified through the four quadrants, as shown in Figure (2). Quadrant I represents the driving attributes, i.e., hose with the greatest influence and greatest importance in their ability to affect other attributes. Quadrant II represents voluntary attributes, i.e., those that have high influence but less importance in their ability to affect other attributes. Quadrant III denotes independent attributes, i.e., those with less influence and less importance. Quadrant IV represents the core problem. Though these attributes have low influence and greater importance, significant improvements could not be achieved through the aspects in this quadrant. Finally, a comparison between the causal diagram of initial information and that of the aggregation of various data sets is conducted to identify the effects of social media, quantitative data and qualitative data in SCRU mitigation.

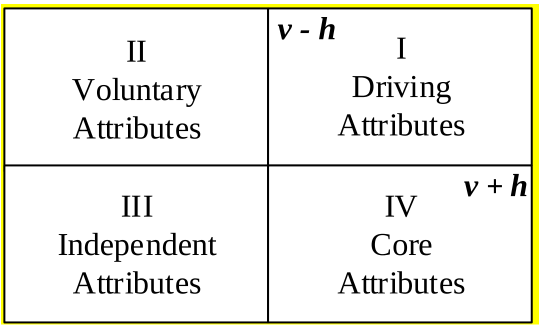

Figure 2. Causal Diagram Quadrant

5. Empirical Results

5.1. Industrial Background

Lighting is a basic human need, but traditional lighting technology generates 1.9 billion tons of CO_2 annually, a statistic that provides a compelling reason to replace traditional lighting with LEDs and thereby reduce CO_2 emissions. Although the Taiwanese industry has a complete supply chain, it lacks the channels and the well-known brands to compete with other countries. More specifically, China's government has subsidized the expansion of local factories to increase their productivity and lower their prices. Moreover, other countries are also aggressively launching relevant subsidized policies to strengthen their local brands and enhance demand in competition.

Many data are generated from these firms' daily operations. However, the manufacturers lack the capability to diagnose risks using these valuable data sets. Furthermore, the industry grapples with high uncertainty due to rapid technological changes and low cost competition. Though firms strive to enhance their capabilities by using the indicators to mitigate risks, limited resources and different aggregated data sets impede firms' abilities address the occurrences of risks and uncertainties. Thus, it is essential to integrate all data when exploring the decisive attributes of SCRU, as this can assist firms in concentrating their resources and investments on strengthening the firms' capabilities to mitigate risks.

5.2. Results

1. Experts employ a linguistic scale to present the importance of aspects in Table 4. However, as the feature of these linguistic scales is qualitative data, it is necessary to use fuzzy set and grey theory to convert the data into comparable values. Table 5 displays the comparison of results from FDM and GDM using Eqs. (7-9) and (18-21), respectively. The aspects are reduced from the original nine aspects to the final seven aspects. Accordingly, Table 6 presents the interactive evaluation of aspects based on the experts' judgments using Eqs. (10-17) and (22-26). These aspects can be mapped into the causal diagram by adopting the coordinates $[(v+h),(v-h)]$, as displayed in Figures (3-4). The diagrams reveal that AS1 and AS3 are the driving aspects for SCRU and that AS5 denotes the core problem.

Table 4. Assessment of Aspects by Experts

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11	E12	E13	E14	E15
A1	1	1	1	3	1	4	1	5	3	2	1	1	3	4	1
A2	4	1	4	4	1	2	1	4	1	4	5	4	4	3	5
A3	1	3	3	3	5	2	1	4	5	5	2	3	5	2	4
A4	2	4	3	2	1	3	5	3	2	4	3	4	4	3	1
A5	3	2	4	3	5	4	5	3	1	3	1	5	1	1	3
A6	4	2	2	5	5	1	3	2	1	3	5	5	3	5	5
A7	4	4	2	2	4	2	3	4	1	5	1	5	3	3	3
A8	4	4	3	2	2	1	2	2	1	4	1	1	1	3	2
A9	4	5	2	3	3	3	5	2	1	4	5	1	4	5	2

Table 5. Comparison of FDM and GDM for Aspects

	FDM		GDM		Renamed	
	S_ℓ	Assessment	$\bar{\bar{\Delta}}G_n^k$	Assessment		
A1	0.2908	x	0.3457	x		
A2	0.3158	0.3158	0.5424	0.5424	AS1	Capacity
A3	0.3175	0.3175	0.5567	0.5567	AS2	Cost
A4	0.3108	0.3108	0.5114	0.5114	AS3	Operation
A5	0.3108	0.3108	0.5083	0.5083	AS4	Reputation
A6	0.3225	0.3225	0.5771	0.5771	AS5	Product
A7	0.2092	x	0.3331	x		
A8	0.3142	0.3142	0.5357	0.5357	AS6	Controllability
A9	0.3192	0.3192	0.5562	0.5562	AS7	Organization
	0.3012	μ_{FDM}	0.4963	μ_{GDM}		

Table 6. Causal Group for Aspects

	FDMATEL				GDMATEL			
	v	h	$(v+h)$	$(v-h)$	v	h	$(v+h)$	$(v-h)$
AS1	22.221	22.154	44.531	0.470	19.560	18.960	38.521	0.600
AS2	22.501	22.030	44.375	0.067	18.867	19.325	38.192	(0.459)
AS3	22.406	22.121	44.527	0.285	19.320	19.013	38.333	0.306
AS4	20.798	20.851	41.649	(0.053)	18.232	18.457	36.689	(0.225)
AS5	21.545	22.046	43.592	(0.501)	18.992	19.646	38.638	(0.655)
AS6	21.968	20.321	42.290	1.647	18.754	17.489	36.243	1.265

AS7	20.504	21.996	42.501	(1.492)	18.190	18.706	36.896	(0.515)

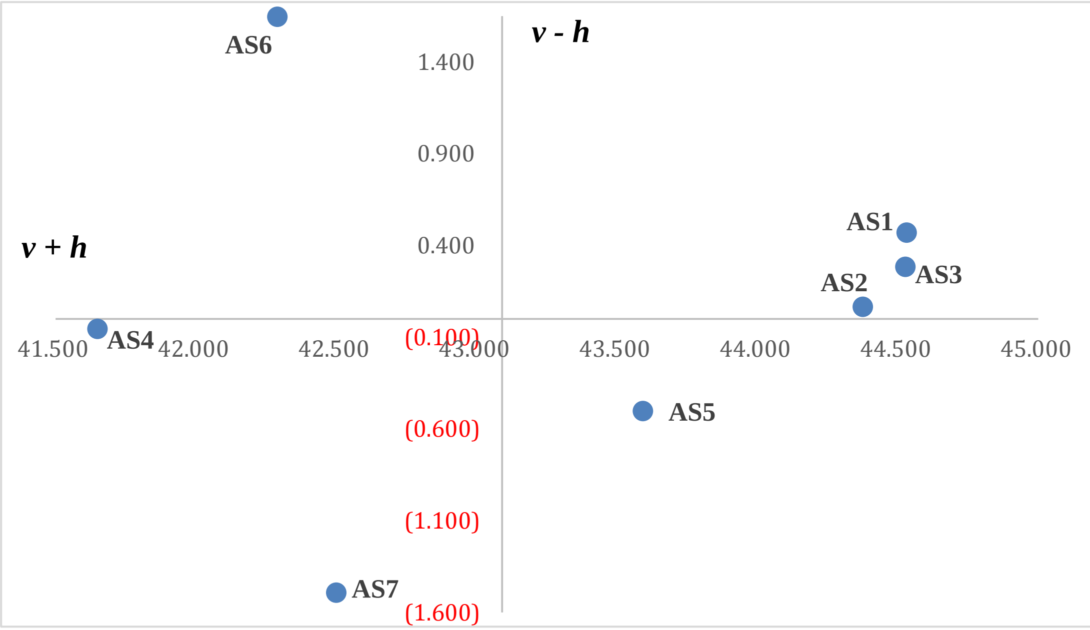

Figure 3. The Causal Diagram for Aspects

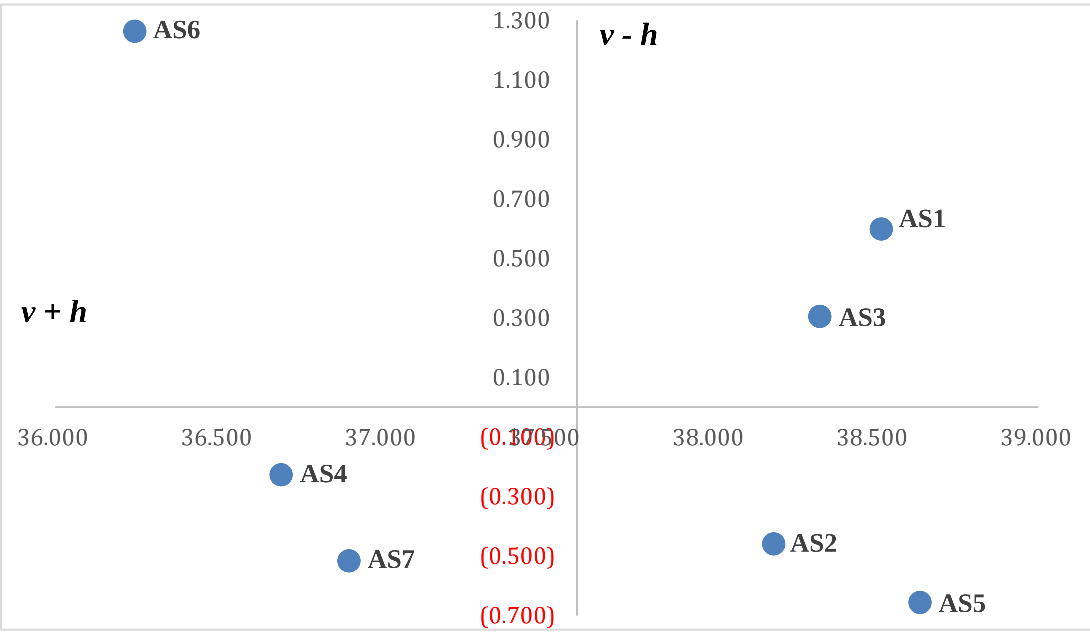

Figure 4. The GDEMATEL Causal Diagram for Aspects

2. Table 7 displays the eliminated result comparison for attributes; 15 attributes remain in the FDM and 16 attributes remain in the GDM. This study adopts 16 attributes for the analysis as the original attribute, C18, had insufficient evidence to support elimination. Subsequently, all remaining attributes are renamed as indicated.

Table 7. Comparison of FDM and GDM for Attributes

	FDM	GDM	Renamed		FDM	GDM	Renamed
C1	x	x		C21	x	x	
C2	x	x		C22	0.320	0.581	C9
C3	x	x		C23	x	x	
C4	x	x		C24	0.329	0.625	C10
C5	x	x		C25	0.331	0.650	C11
C6	0.316	0.546	C1	C26	0.333	0.660	C12
C7	x	x		C27	x	x	
C8	0.355	0.578	C2	C28	x	x	
C9	0.316	0.536	C3	C29	x	x	
C10	0.331	0.643	C4	C30	x	x	
C11	x	x		C31	0.316	0.539	C13
C12	x	x		C32	0.362	0.609	C14
C13	x	x		C33	x	x	
C14	x	x		C34	x	x	
C15	0.318	0.553	C5	C35	x	x	
C16	0.321	0.588	C6	C36	0.326	0.626	C15
C17	x	x		C37	x	x	
C18	x	0.532	C7	C38	0.326	0.597	C16
C19	x	x		μ_{FDM}	0.315		
C20	0.323	0.598	C8	μ_{GDM}		0.529	

3. Social media data are acquired through public and professional websites to accumulate frequencies of the proposed aspects. In addition, the quantitative data are obtained from firms' financial statements and operational data (total 1,951,749 sets of data). The transformations are derived by applying Eqs. (1-6) and are presented in Table 8.

Table 8. Entropy Weights and Quantitative Transformations

	Frequency	Ratio	Normalize	Entropy	Entropy Weight	Quantitative Transformation
C1	2549	0.0907	0.0785	0.9215	0.0613	0.4253
C2	801	0.0285	0.0366	0.9634	0.0641	0.3993
C3	1517	0.0540	0.0568	0.9432	0.0627	0.3764
C4	1486	0.0529	0.0561	0.9439	0.0628	0.3814

C5	1869	0.0665	0.0650	0.9350	0.0622	0.3962
C6	2745	0.0977	0.0820	0.9180	0.0611	0.4738
C7	1777	0.0633	0.0630	0.9370	0.0623	0.2457
C8	2479	0.0882	0.0773	0.9227	0.0614	0.6145
C9	2759	0.0982	0.0822	0.9178	0.0611	0.2090
C10	2110	0.0751	0.0701	0.9299	0.0619	0.1658
C11	1124	0.0400	0.0464	0.9536	0.0634	0.1902
C12	2154	0.0767	0.0710	0.9290	0.0618	0.4834
C13	1874	0.0667	0.0651	0.9349	0.0622	0.7428
C14	1631	0.0581	0.0596	0.9404	0.0626	0.0865
C15	900	0.0320	0.0398	0.9602	0.0639	0.1657
C16	319	0.0114	0.0183	0.9817	0.0653	0.6361

4. The FDEMATEL and GDEMATEL are based on Eqs. (10-17) and (22-26), respectively. The entropy weight and quantitative transformation should be integrated with the computations of the FDEMATEL and GDEMATEL. Table 9 presents the aggregated causal group for attributes.

Table 9. Aggregated Causal Group for Attributes

	FDMATEL				GDMATEL			
	v	h	$(v+h)$	$(v-h)$	v	h	$(v+h)$	$(v-h)$
C1	0.6366	0.7009	1.3374	(0.0643)	0.5390	0.6041	1.1431	(0.0651)
C2	0.5587	0.6567	1.2154	(0.0980)	0.4853	0.5620	1.0473	(0.0767)
C3	0.6266	0.6088	1.2354	0.0178	0.5440	0.5208	1.0648	0.0232
C4	0.6242	0.6142	1.2384	0.0100	0.5462	0.5261	1.0723	0.0201
C5	0.6433	0.6427	1.2860	0.0006	0.5513	0.5498	1.1011	0.0015
C6	0.6322	0.7653	1.3975	(0.1332)	0.5390	0.6508	1.1898	(0.1119)
C7	0.6219	0.3962	1.0180	0.2257	0.5201	0.3409	0.8611	0.1792
C8	0.6108	0.9623	1.5731	(0.3515)	0.5224	0.8259	1.3483	(0.3035)
C9	0.6155	0.3250	0.9405	0.2905	0.5209	0.2783	0.7991	0.2426
C10	0.5829	0.2638	0.8467	0.3191	0.5050	0.2259	0.7309	0.2791
C11	0.6301	0.3186	0.9486	0.3115	0.5364	0.2726	0.8091	0.2638
C12	0.6205	0.7965	1.4170	(0.1760)	0.5286	0.6855	1.2142	(0.1569)
C13	0.5805	1.1925	1.7731	(0.6120)	0.4917	1.0241	1.5158	(0.5324)

C14	0.6074	0.1360	0.7434	0.4714	0.5306	0.1162	0.6468	0.4144
C15	0.5762	0.2755	0.8518	0.3007	0.4950	0.2370	0.7319	0.2580
C16	0.5741	1.0864	1.6605	(0.5123)	0.4925	0.9281	1.4206	(0.4356)

5. The causal diagram is mapped based on the coordinates $[(v+h),(v-h)]$ in Table 9. Once the mapping is completed, the decisive attributes of SCRU are explored in Figures 5 and 6. These figures, aggregated with the big data, social media data and qualitative data, therein, C3, C4 and C5, are the driving attributes for mitigating SCRU as greater influence is ascribed to other attributes. Moreover, these attributes, C1, C6, C8, C12 and C16, are located in the quadrant of the core problem, which represents an essential need for improvement, though the improvement processes must amend the driving attributes.

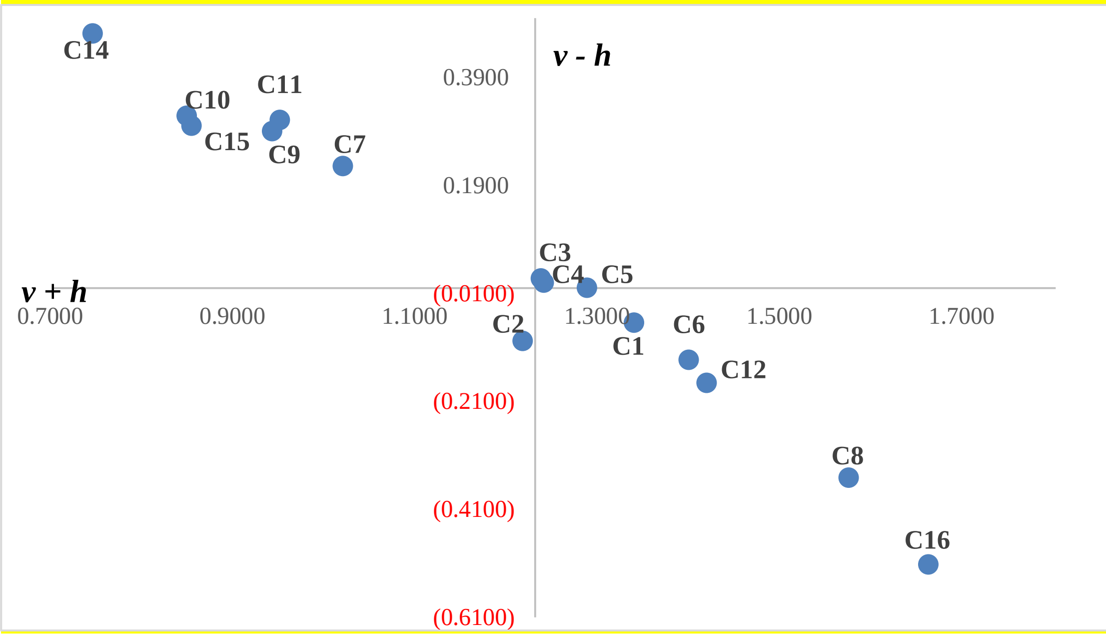

Figure 5. The FDEMATEL Causal Diagram According to Various Data Aggregations

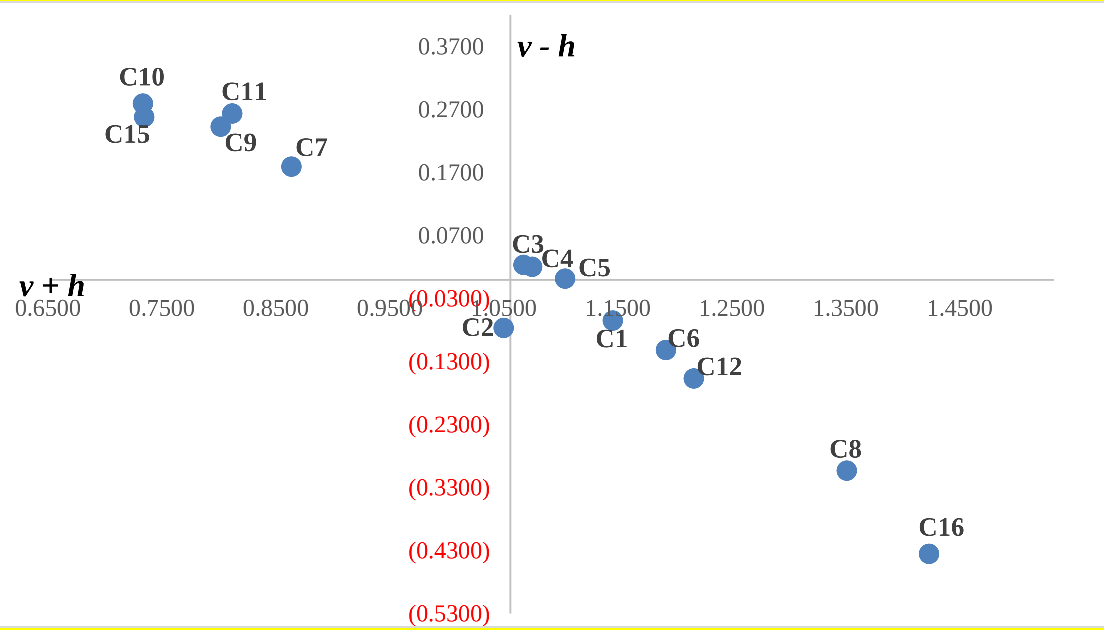

Figure 6. The GDEMATEL Causal Diagram According to Various Data Aggregations

6. Compare the causal diagram with the initial judgments of the experts (see Figures (7-8) to identify the effects of aggregating the different data sets and enhancing the accuracy in decision making. This confirms that C3, C4 and C5 are the driving attributes of SCRU, according to Figures (5-8). In addition, the results indicate that C12 is in need of urgent improvement.

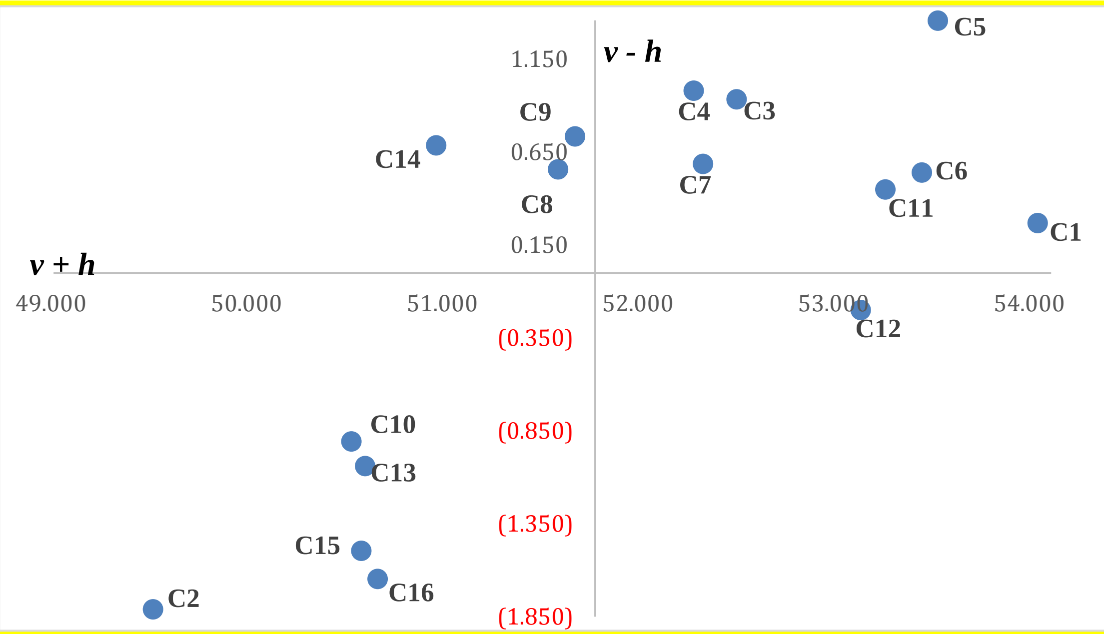

Figure 7. The FDEMATEL Causal Diagram

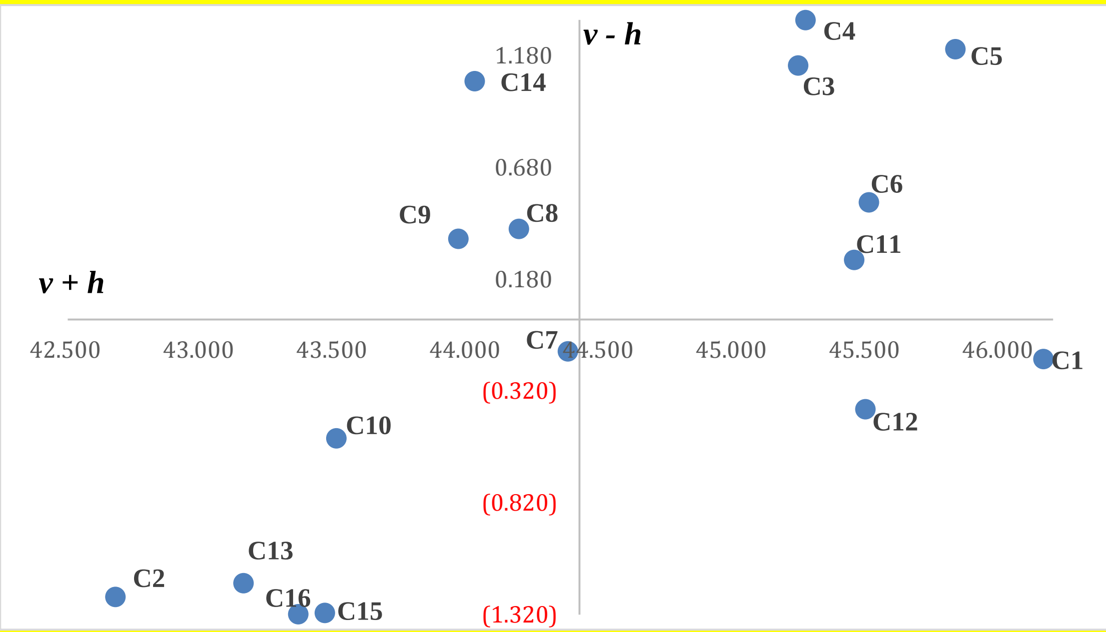

Figure 8. The GDEMATEL Causal Diagram

6. Theoretical and Managerial Implications

Based on the empirical results, significant insights into the theory and its implementation contribute to the understanding of SCRU. From such insights, firm managers can guide firms in establishing the capabilities necessary to confront risks and uncertainties.

6.1. Theoretical Implications

Capacity (AS1) has the greatest influence of any factor on SCRU. Therefore, capacity must be developed to reduce the occurrence of risk. Previous studies stress that flexible capacity mitigates the risks of excess capacity, particularly in terms of reducing idle capacity and creating a flexible production line (Atwater et al., 2014; Chopra & Sodhi, 2004). However, increasing flexibility in capacity requires additional investments. Thus, the results suggest that another way to improve capacity is through margin improvement as the margin acts as a buffer to assist firms in mitigating the occurrence of risky events and in absorbing loss. Moreover, if firms are able to improve their margins, the cost of capacity might be reduced simultaneously. This result reflects the real situation of Taiwanese LED industry is striving for improving the margin, particularly, LED manufacturers are launching product innovation to increase the value for customers.

Operational risks (AS3) cover several areas of potential failure in the supplier to customer chain, and thus, if firms can prevent operational risks, they have a good opportunity to thwart other risks. Accordingly, firms must maintain good labor relations to enhance their success in preventing risks, which emphasizes the point that labor problems can cause operational risks in terms of poor quality, low productivity and unfilled orders (Jiang et al., 2009). In addition, maintaining labor relations not only reduces turnover intentions but also enhances the firm's reputation. Hence, the well-known Taiwanese LED firms realize that the operational risk is a critical negative impact among the firm. In order to ensure the operation sticks with the standard of procedure and avoid the risk occurrence, these firms provide series of training and developing course for their labors, so the labors enable to improve their skills in the operation or develop a new skill to make the operation efficiently.

While prior studies find that capacity (AS1) and operation (AS3) may generate supply chain risks, they are unable to identify the driving factors that will reduce such occurrences. This study aggregates social media, quantitative data and qualitative data to extensively reflect the impact on decision making, and it utilizes collaboration theory to demonstrate the interactions. The prevention of risk is achieved through alignment, which requires maintaining consistency with respect to needs. However, it is difficult to mitigate risk by adopting congruence as the probability of such congruence due to these attributes is highly uncertain and unpredictable.

6.2. Managerial Implications

Margin improvement (C3) is one of the driving attributes behind the prevention of SCRU. Most firms consider margin improvement as a way to increase profit; however, the key purpose is to establish a buffer to effectively absorb or defend against loss when a risky event occurs. Although most Taiwanese LED firms are profit oriented, they employ a specific technique to improve operational efficiency but often ignore the establishment of a buffer in the profit margin to prevent risks. Once a risky event occurs, many firms merge or are acquired by larger firms and hence must use their specific technique to develop and extend their capabilities into a core competitive advantage. This core competitive advantage should be adapted to respond to rapid market changes rather than to low cost competition.

Furthermore, employee education and skills development (C4) is a double-edged sword in that unexpected innovation and improvement generated through education and skill development for employees, while increasing the firm's human capital, come at a cost to the firm. Thus, this practice is still lacking in the industry due to limited investments and resources. However, over the long term, firms must establish educational programs for their employees and provide opportunities for them to develop and enhance their skills as sufficient education and skill create flexibility in production and generates a dynamic for responding to customer feedback.

LED firms focus on profit while neglecting the impacts of labor relations (C5). Significantly, the empirical results recognize that this problem may be related to SCRU. Labor problems cause organizational friction, generate unstable skills and negatively impact customer satisfaction, factors that lead to high employee turnover. Conversely, such turnover can be prevented by educating employees and thereby enhance firm performance. In the long term, stable employee turnover generates a positive impact, particularly in terms of novel ideas and rapid information sharing among the supply chain networks. However, decreasing turnover reduces short term SCRU.

These firms are capable of conquering firm capability development by identifying the big data to enhance their accuracy in mitigating SCRU for the decision-making process. The results reveal that firms can enhance their building capabilities, e.g., margin improvement (C3), employee education and skills development (C4), and labor relations (C5). Moreover, it is necessary to increase and improve product stewardship (C12), and this improvement is ameliorated through the three driving attributes. Once firms succeed in strengthening their capabilities, they will be able to mitigate unintentional risks.

7. Conclusions

The Taiwanese LED industry proposed to adopt sustainability indicators to prevent SCRU. Although the indicators provide firms with a guideline toward sustainability, the firms often underinvest in developing their capabilities. Furthermore, the firms experience difficulties in determining the risks and uncertainties due to limited resources and inadequate approaches to aggregate the different data sets. Hence, this study attempted to eliminate the lesser important attributes in the Taiwanese LED industry and proposed aggregating the big data into the decision matrix. Subsequently, FDEMATEL and GDEMATEL were used to explore the decisive attributes in mitigating the SCRU. Finally, the comparisons of the proposed methods are essential for enhancing the accuracy and reliability and confirming the decisive attributes as firms may strengthen the capabilities and mitigate the risks and uncertainties by concentrating their resources and investments in these attributes.

The contribution of this study is to offer guidelines for LED firms to reduce the risks and uncertainties by effectively utilizing the resources and investments while developing the sustainability. With respect to theoretical implications, capacity and operations are the driving aspects, thus confirming their influence as identified in previous studies and supporting the evaluation of their attributes. As firms provide flexible capacity and beneficial effects through alignment and congruence, similarly, operations must adopt several controls for improvement where the productions are located in the core problem quadrant. In addition, though most risks and uncertainties can prevent functional risks, trigger events are difficult to prevent given that they are generally unintentional and unpredictable.

The remaining attributes located in the first quadrant represent significant decisive attributes that lead firms to mitigate the risks including margin improvement, employee education, skills development and labor relations. Margin improvement establishes a buffer and absorb loss when risks occur. Though employee education and skills development are costly, if an employee integrates the new knowledge and skills and thereby improves firm efficiency and effectiveness, the occurrence of risky events will be prevented. Labor relations allow firms to achieve efficiency in operations. However, as increasing product stewardship is a major challenge and it is difficult to meliorate the performance, the improvement must include the investment of resources into three decisive attributes.

Several limitations exist regarding this study. Although the proposed attributes are acquired through extensive literature reviews, the basis is still insufficient to cover all attributes. Hence, the eliminating assessments could include more attributes in future research. In addition, the selected information only focused on the Taiwanese LED industry as doing so allowed us to control the contextual and operational attributes in the industry. However, it also limits the generalizability of the findings. Future studies could expand this study to other industries and thus overcome the limitations regarding generalizability. Furthermore, implementing sustainability is crucial for Asian manufacturers because of the nature of complexity in the supply chain networks. To assist firms in preventing risks due to uncertainty, future research should investigate the precise relationship between firms' capabilities and the SCRU.

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