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Reverse Logistics Risk Management; Identification, Clustering, and Risk Mitigation Strategies

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Abstract

Purpose- Reverse Logistics (RL), an inseparable aspect of supply chain management, returns used products to recovery processes with the aim of reducing waste generation. Enterprises, however, seem reluctant to apply RL due to various types of risks which are perceived as posing an economic threat to businesses. This paper draws on a synthesis of supply chain and risk management literature to identify and cluster RL risk factors and to recommend risk mitigation strategies for reducing the negative impact of risks on RL implementation.

Design/methodology/approach- The authors identify and cluster risk factors in RL by using risk management theory. Experts in RL and supply chain risk management validated the risk factors via a questionnaire. An unsupervised data mining method, Self-Organising Map (SOM), is utilised to cluster reverse logistics risk factors into homogeneous categories.

Findings- 41 risk factors in the context of RL were identified and clustered into three different groups: strategic, tactical, and operational. Risk mitigation strategies are recommended to mitigate the RL risk factors by drawing on supply chain risk management approaches.

Originality/value- This paper studies risks in RL and recommends risk management strategies to control and mitigate risk factors to implement RL successfully.

Keywords: Reverse Logistics, Supply Chain Management, Risk Management, Clustering, Self-Organising Map, Risk Factors

1 Introduction

Population growth, radical technological changes, and the diversification of products and services have led to tremendous raw material extraction, excessive consumption, and massive waste generation (Efendigil et al., 2008; Govindan and Bouzon, 2018; Govindan and

Hasanagic, 2018; Khor and Hazen, 2016; Prajapati et al., 2019). A short product life cycle combined with mass consumption results in significant waste generation and places pressure on societies to develop innovative and sustainable ways to preserve the environment against pollution and unnecessary creation of landfill (Bouzon et al., 2016; Lambert et al., 2011).

Reverse Logistics (RL) offers a solution through product recovery methods. Whilst RL has not been systematically or particularly widely implemented, it has attracted the attention of academics and practitioners over the last two decades (Bouzon et al., 2016; Huang et al., 2015; Huscroft et al., 2013; Mangla et al., 2016; Sarkis et al., 2010). RL can be defined as "*all logistical operations including planning, implementing, and controlling the efficient cost-effective flow of raw materials, in process inventory, finished goods, and related information from the point of consumption to the point of origin for the purpose of recapturing or creating value or proper disposal*" Rogers and Tibben-Lembke (1999, p. 130). Unlike traditional forward logistics, RL focuses on returning products at the end of their useful life to recapture value and reduce environmental pollution (Bensalem and Kin, 2019; Chan et al., 2012; Dowlatshahi, 2010; Hansen et al., 2018; Subramanian et al., 2014).

Economic benefits, such as lowering costs and achieving corporate social responsibility goals, are strategic drivers which motivate firms to adopt RL practices (Agrawal et al., 2015; Morgan et al., 2018). In some countries, product take back legislation obligates manufacturers to instigate RL processes and, more broadly, the efficient management of return flows has emerged as a major concern in RL. Manufacturers are facing difficulties with effective implementation of RL, mainly due to operational complexities and a lack of relevant experience (Bai and Sarkis, 2013; Halldórsson et al., 2010; Mangla et al., 2016). There are organizations which consider RL as an "evil" rather than an opportunity; perceptions which may arise from a lack of clarity about risks and economic benefits (Mahadevan, 2019). Furthermore, recovered products have the potential to cannibalise markets by competing with new products in terms of quality, quantity, and value (Panjehfouladgaran et al., 2018; Turrisi et al., 2013).

These risks might be affecting the success of RL, making risk management an important aspect of any organization (Cagliano et al., 2012; Gaudenzi and Borgheshi, 2006; Khan et al., 2008 Scheibe and Blackhurst, 2017; Wiengarten et al., 2016). The importance of risk management in RL relies on increasing the value for the supply chain in a reverse direction by means of mitigating the risks and decreasing the negative environmental impacts and cost. Researchers have studied supply chain risk management in order to prevent severe negative impacts on the organizations, but there is very limited research on Reverse Logistics Risk Management (RLRM). The majority of this research is focused on a specific area of RL such as optimisation of RL network design (El-Sayed et al., 2010; Soleimani and Govindan, 2014; Rahimi and Ghezavati, 2018; Senthil et al. 2018), production planning (Amini et al., 2005; Bogataj and Grubbstrom, 2013; Zarbakhshnia et al., 2018;), and the environment (Khor et al., 2016; Khor and Hazen, 2016). Hence, RLRM is an emerging field within supply chain management (SCM), with risk identification, as well as risk classification still under-explored (Ageron et al., 2012; Hall et al., 2013).

Therefore, this paper is aiming to bridge the gap of knowledge by first identifying RL risk factors and then classifying risks into homogeneous groups. Risk identification provides the opportunity for decision makers to develop mitigation strategies to reduce the negative impact of risk on organisational performance. However, providing risk mitigation strategies for individual risks is costly and is often impossible due to the sheer number of risks that can be identified. Therefore, categorising risks into homogeneous groups with similar characteristics would allow decision makers to mitigate a group of risks through a minimum number of risk mitigation strategies. Thus, the questions that frame this research are as follows:

RQ1: What are the relevant risk factors in RL?

RQ2: How can the risk factors be categorised in a manner which is useful to Operations Managers?

In this research, we first identify the risk factors by reviewing the literature related to RL, logistics, risk management, and supply chain management. The relevance of the risk factors to RL is verified through a questionnaire administered to a panel of logistics and RL experts. Then, we examine the possible clustering of these factors into categories, based on clustering using a Self-Organising Map (SOM). The SOM technique is particularly appropriate for clustering under conditions of a relatively small, non-linear (Allahyar et al., 2015; Kohonen, 2013; Sulkava et al., 2015), and random dataset (Bação et al., 2004). The SOM technique offers improved performance in terms of accuracy and sensitivity when compared to other prevalent techniques such as k-means, hierarchical clustering, and expectation maximising clustering (Abbas, 2008; Mangiameli et al., 1996; Mingoti and Lima, 2006).

The paper is organised as follows. Section 2 reviews the key literature. Section 3 describes the adopted methodology. Section 4 identifies the key risk factors and their clusters, while in-depth discussion of their relevance is presented in Section 5. Section 6 presents a strategic framework for risk mitigation. Section 7 highlights the implications for research and practice, with the conclusion and future research directions presented in the last section.

2 Literature Review

2.1 Reverse Logistics

RL is a relatively new term (Mangla et al., 2016). It focuses on waste management and product recovery and has immense potential for increasing profit (Lambert et al., 2011; Luthra et al., 2017; Stindt et al., 2017). RL includes all logistics activities that enable the returns of used products in order to recapture value or implement proper disposal. Repair, recycling, reuse, remanufacturing, and refurbishing are some of the basic processes in RL which manufacturers are responsible to perform in the reverse flow (Fleischmann et al., 1997; Rogers and Tibben-Lembke, 2001; Govindan and Soleimani, 2017; Khor et al., 2016; Prajapati et al., 2019).

Managing RL is a complex operation due to the diverse range of activities vis-a-vis forward logistics (Amini et al., 2005). Forward logistics concerns material flow from raw material to the end product and from supplier to final consumer while RL concerns the flow of used materials and products from the final consumer to manufacturers and suppliers (Kannan Govindan and Soleimani, 2017; Hansen et al., 2018). The complexity of RL arises from the quality of returned products, low standardization, and more manual processes, while forward logistics activities are more standardised with higher quality products (Hansen et al., 2018; Jaaron and Backhouse, 2016). However, RL can potentially improve forward logistics performance (Govindan and Soleimani, 2017; Hansen et al., 2018; Kocabasoglu et al., 2007). A summary of the differences between forward and RL in the retail environment is presented in Table 1 (Tibben-Lembke, 2002).

<< TABLE 1 ABOUT HERE >>

Due to the differentiation of reverse and forward logistics, as highlighted in Table 1, RL is risky. Returned products in RL could be collected from different points of consumption in various states of repair. Products might be returned due to consumers' willingness for product recovery or damages, incorrect merchandise, errors in order picking or suitability in addressing consumer's needs. Despite forward logistics, the pricing for the products in RL is not following certain rules or procedures. The price of returned products depends on various factors such as the consumers' behaviour, early and quick disposition of used products, and equipment for the logistics movement. Therefore, pricing of recovered products and other sources of risk are potential barriers for implementation of RL. All aforementioned issues result in accumulated risks for those companies which are implementing RL as their core operations (Bogataj and Grubbström, 2013; Pokharel and Mutha, 2009).

It is important to identify and manage relevant risk factors. As RL is a part of supply chain management, RL risk management could be studied to generate research areas that provides insight for further knowledge, concepts, theories and relevant tools and techniques (Ageron et al., 2012; Aven, 2016; Behzadi et al., 2018; Fahimnia et al., 2015; Hall et al., 2013). Stock and Lambert (2001) highlight the potential risks of utilizing the same equipment for product movement in forward and RL, and Srivastava (2008) identifies some risk types, such as quality, quantity, and cost. From a theoretical perspective, more clarity is required on the types of risk factors in RL. Given the scarce literature on risk factors in RL, we examine the literature bodies within risk management and supply chain risk management (SCRM) to identify risk factors that are relevant for use in RL.

2.2 Risk Management

Risk has two basic components: a future outcome, for example, a supplier increasing the price of a product, and the probability of a particular outcome (Khan and Burnes, 2007). Ellegaard (2008) argues that risk management increases knowledge, thus reducing the likelihood of risks occurring and the effects of risks on processes, since companies are likely to work more successfully against risks if they are aware of them *a priori*.

Risk management comprises three critical steps: identification, classification, and evaluation (Abdel-Basset et al., 2019; Cagliano et al., 2012; Fan and Stevenson, 2018;

Gaudenzi and Borghesi, 2006; Khan and Burnes, 2007; Prakash et al., 2017; Rao and Goldsby, 2009). Identification involves determining all possible risks in a particular subject. In classification, risks are categorised into homogeneous groups for subsequent investigation and risk mitigation strategies. In risk evaluation, managers decide how to respond to the identified risks (Fan and Stevenson, 2018; Giannakis and Papadopoulos, 2016; Ho et al., 2015; Khan et al., 2008; Lavastre et al., 2012). In accordance with risk management standards, Gaudenzi and Borghesi (2006) highlighted the four key steps in risk evaluation: (1) risk assessment, (2) risk reporting and decision-making, (3) risk treatment, and (4) risk monitoring.

Scholars have attempted to refine this generic process and developed risk management frameworks for application in SCM with particular focus on considering risk mitigation strategies (Abdel-Basset et al., 2019; Chang et al., 2015; Chen et al., 2013; Christopher and Lee, 2004; Lavastre et al., 2014; Tummala and Schoenherr, 2011; Zsidisin and Hartley, 2012). Several scholars emphasise the importance of aligning risk strategies with risk types and sources (Chopra and Sodhi, 2004; Oke and Gopalakrishnan, 2009). For example, Shah (2009) suggests hedging, contract design, and robust network design as mitigation strategies on supply cost uncertainty, while Zsidisin and Hartley (2012) propose substituting, forward buying, and cross hedging as mitigation strategies to deal with commodity price risks.

Classical risk management techniques seek to understand the risks associated with prevention, enact monitoring processes to reduce the impact and mitigate risks by means of transferring them to or sharing them with other parties, as well as through product diversification (Diabat et al., 2012; Khan and Burnes, 2007). Our literature review reveals three general classifications of techniques for analysing risks: qualitative, quantitative, and control. Qualitative techniques aim to detect, describe, and analyse risks (Cagliano et al., 2012; Ghadge et al., 2017; Ho et al., 2015; Juttner et al., 2003). In quantitative techniques, researchers search for a model to interpret and measure risks' effects (Behzadi et al., 2018; Fahimnia et al., 2015; Lockamy and McCormack, 2010; Mehrjoo and Pasek, 2015). Control techniques examine identified risks with the intention of mitigating risk exposure (Christopher and Lee, 2004; Manuj and Mentzer, 2008).

2.3 Supply Chain Risk Management

Tang (2006) defines SCRM as a collaboration between supply chain members to reduce risk and increase profitability. SCRM is therefore a continuous process that requires long-term commitment from members (Giunipero and Eltantawy, 2004; Grötsch et al., 2013) as it can affect the operational and financial aspects of the firm (Khan and Burnes, 2007)According to Ritchie and Briendley (2007), SCRM consists of risk drivers, risk management influencers, decision maker characteristics, risk management responses, and performance outcomes. From a management perspective, Juttner et al. (2003) propose four aspects: (1) supply chain risk sources assessment; (2) defining supply chain adverse incidences; (3) supply chain risk drivers; and (4) supply chain risk mitigation.

The scientific development in SCRM is extensive, with researchers focusing on different management aspects:

<< TABLE 2 ABOUT HERE >>

A common theme around these varied studies is the fundamental identification of risk factors or the sources of risks. Not surprisingly, much effort has been devoted to the identification of relevant risk factors in SCM so as to trigger proactive or reactive mechanisms. Proactive risk mitigation strategies concern preventing risk. In contrast, reactive risk mitigation strategies prepare for the occurrence of a risk event to alleviate its economic impact. For example, Giunipero and Eltantawy (2004) identify some factors that could impact on SCRM: demand fluctuations, product availability, manufacturer capacity, and financial stability (Giunipero and Eltantawy, 2004). Rao and Goldsby (2009) classify some organisational risks based on their sources: environmental, industry, organisational, and problem-specific factors. Tang (2006) divides risk factors into operational and disruptions. Operational risk factors refer to those that are inherently uncertain, such as customer demand and costs. Disruption risk factors are associated with major risks caused by natural or man-made disasters like earthquake, hurricanes, flood, terrorist attack, or economic crises. Fischl et al. (2014) classify risks into supply, procurement, purchasing, and sourcing.

Given the depth of knowledge in terms of risk factors in this domain, we undertake an extensive review of the literature to identify the common sources of risk in supply chain and forward logistics. Table 3 illustrates seminal papers in the supply chain and logistics risk management domain which have identified risk factors. These studies have used the publications in the related field. While we have identified several risk factors from the SCRM domain, knowledge of their relevance and application in RL is inadequate due to the limited attention given to examining the theoretical development of risk factors in RL. Our study directly addresses this gap by investigating the relevance of these risk factors in RL, which is essential given the increasing importance of the RL

<< TABLE 3 ABOUT HERE >>

Previous literature studied the convergence of Supply Chain Management (SCM) and risk management (RM) known as Supply Chain Risk Management (SCRM). However, there is a gap of study on the convergence of RL with RM. Since RL originates from SCM, there is an opportunity to integrate the domains of these three theoretical lenses to identify the critical risk factors relevant to RL and advance the theoretical development within the field (see Figure 1). For the purpose of this study, we call the research field at the intersection of SCRM and RL as Reverse Logistics Risk Management (RLRM).

<< FIGURE 1 ABOUT HERE >>

3 Research Method

3.1 Risk Identification in Reverse Logistics

The methodology of this research is illustrated in Figure 2. In the first step, risk factors in SCM were extracted from the literature. 115 risk factors were identified from the SCM and Logistics domain. Then, two academic experts (Govindan et al., 2015; Sangari and Razmi, 2015) in SCM and Logistics with minimum five years' experience were selected to combine risk factors in SCM based on their definitions and their similarities in content or title. The combinations of the risk factors were done for simplification and to preventing duplication. This first step resulted in an output of 42 risk factors.

In the second step, a questionnaire was designed based on the 42 risk factors for validation. The purpose of validation in this step was to ensure a high level of quality was achieved. The level of quality in this research is related to the accuracy of the risk factors which does not follow statistical rules. According to Di Zio et al. (2017), using the Experts' opinion on its own is a way of judging the validation level of data. Hence, conducting expert sampling negates the need for further validation in this study. Therefore, this study applied judgmental sampling which is the most effective approach when a limited number of individuals (in this case, experts) possess the trait that a researcher is interested in. RL experts indicated “Yes” or “No” to each factor in terms of its relevance to RL.

If they indicated “Yes”, they were then asked to provide a significance rating on a five-point Likert scale with “5” being “very important” and “1” being “not important”. The value of accepted RL risk factors was used for clustering of the factors using the SOM approach in the third step.

The questionnaire was sent via email to 255 corresponding authors of SCRM and logistics risk management papers. All respondents were academics and practitioners with a minimum of five years’ experience in the related field. Twenty-two experts responded to the questionnaire (Habermann et al., 2015) via email. The distribution of the respondents is summarised in Table 4. With the consolidated results, we assessed the level of agreement with the RL risk factors by testing the null hypothesis.

<< TABLE 4 ABOUT HERE >>

The binomial statistical test is used to check the null hypothesis. A “Yes” response is coded as “1” while a “No” is coded as “0”. Hence, the hypothesis is defined as:

$$H_0: Mean = 0.5 \quad (1)$$

$$H_1: Mean \neq 0.5 \quad (2)$$

<< INSERT FIGURE 2 ABOUT HERE >>

3.2 Clustering by Self-Organising Map (SOM)

In the third and final step, the investigation employs a data-mining method of clustering the risk factors in RL using the SOM approach, a heuristic clustering method based on unsupervised clustering algorithms introduced by Kohenen in 1981 that is capable of mapping high dimensional data into low dimensional elements for better visualisation. SOM is a heuristic clustering method which utilises artificial neural networks for its computation

(Allahyar et al., 2015; Chaudhary et al., 2014; Kohonen, 2013). While various other techniques for clustering exist in the literature (e.g. k-means, hierarchical clustering, and expectation maximising clustering), the SOM approach is particularly appropriate for clustering under conditions of relatively smaller size, non-linear (Kohonen, 2013) and random datasets; the sort of data collected in this study (see Table 5) (Bação et al., 2004). In terms of accuracy and sensitivity performance, the SOM appears to perform better than the other three techniques mentioned above (Abbas, 2008; Mangiameli et al., 1996; Mingoti and Lima, 2006). Our sample size is consistent with other works in the management domain e.g. (Länsiluoto and Eklund, 2008) and in other disciplines e.g. (Krasznai et al., 2016) which has adopted a similar approach with low sample size and yet achieved relatively good accuracy.

<< INSERT TABLE 5 ABOUT HERE >>

3.2.1 Principle of SOM

The architecture of SOM contains a set of units that are arranged in a 2D grid of neuron nodes. Each node has the same dimension as the input vector and weights are initialised randomly (Allahyar et al., 2015; Kohonen, 2013). Figure 3 depicts the architecture of SOM, where X is an input that broadcasts to a set of data and M_i is the best match with X. The large circle encompassing multiple neuron nodes shows a grid of nodes that are close to the input data based on the SOM algorithm. Therefore, SOM works based on a competitive learning approach, i.e. a function of distance between neuron weight and input data. Subsequently, if a similar pattern is identified the second time, the same neuron nodes are reactivated another time (Chaudhary et al., 2014). Figure 4 further illustrates the SOM architecture for the “n” continuous vector into “m” cluster.

<< INSERT FIGURE 3 ABOUT HERE >>

<< INSERT FIGURE 4 ABOUT HERE >>

In general, the application process of SOM for clustering can be described in the following five steps (Azadnia et al., 2012; Karray and De Silva, 2004; Vesanto and Alhoniemi, 2000):

Step 1 (Initialization): In the first step, each vector is assigned to its own cluster. The weights of each node and learning rate in this step would be determined. Calculations of distances between all clusters are based on the Euclidean distance formula. The Euclidean distance is given as:

$$d_j = \sqrt{\sum_{i=1}^{n}(x_i - w_{ij})^2} \qquad (1)$$

Step 2: Select the winning unit "c" which is the best matching output unit. The Euclidean distance should be minimised based on the input pattern "x" to "w_{ij}".

$$d = \|x - w_c\| = min_{ij} = \|x - w_{ij}\| \qquad (2)$$

Step 3: Update the weights based on the global network. Updating should start from "k" to iteration k+1 as follow:

$$w_{ij}(k+1) = w_{ij}(k) + \alpha(k)\left[x - w_{ij}(k)\right] \; if \; (i,j) \in N_c(k) \qquad (3)$$

$$w_{ij}(k) \qquad \text{otherwise}$$

where α is the learning rate and $N_c(k)$ is the neighborhood of the unit "c" at the iteration "k".

Step 4: In this step, the learning rate and neighbourhood is decreased at each iteration.

Step 5: In the fifth and final step, the iteration continues until all the clusters are occupied by the dataset or when all the data have shifted from one cluster to another stop.

3.2.2 Procedure

Given the preceding detailed description on the application procedure of SOM for clustering, we now conduct the procedure on our dataset. Firstly, the number of clusters is randomly initialised as 10, which increases if all of the 10 clusters are utilized by the risk factors. Secondly, the primary learning rate for the method considered is 0.01 in order to decrease severe changes in neurons of the external layer, and the neighbourhood distance considered is equal to the length of three neurons in order to increase the efficiency of the algorithm. If one of the risk factors is absorbed by a winning neuron, the weight of the rest of the neurons will be updated as 0.95 the weight of the winning neuron. Therefore, the chance of the neighbourhood neurons absorbing a risk will increase. Lastly, the maximum number of iterations considered is 20 learning periods (epoch), which could be increased depending on the stability of the model. The labels of the risks are different because the weights of the neurons in the external layer are produced randomly. However, similar risks in a cluster would have the same label in the next epoch.

This research adopts the method suggested by Khalid (2011) to validate the clustering accuracy and stability using two evaluation techniques: (1) Stability of the clustering across the samples; and (2) External validation. The first evaluation technique is programmed using MATLAB® software. Stability evaluation is defined based on the number of iterations and data shifting from one cluster to another (Mangiameli et al., 1996; Mingoti and Lima, 2006). Once the data shifting process ceases, it indicates that the number of clustering has reached stability.

For external validation, statistical procedures are applied to determine the variation of data within the clusters. We used SPSS software to validate the clustering by employing the Analysis of Variance (ANOVA) technique, which facilitates the comparison of variance between a number of groups and can therefore measure the level of significance between the clusters. It compares two types of variance: between group sum of squares, and within group sum of squares. More specifically, the ANOVA technique is employed to examine whether or not the clusters are significantly different using an alpha value of 0.05. Therefore, if the variance of the group means is significantly greater than predicted, the means of the groups are different.

4 Findings

4.1 Identified Risk Factors in RL

The identified risk factors in RL and their descriptions are provided in Table 6. The first column details the list of 42 factors, and the second displays the percentage of agreement to each factor. The third column indicates the percentage of disagreement of the relevance of each factor to RL. The fourth column specifies the test proportion at the 0.5 level and the final column highlights the exact results of the test.

For example, looking at the first risk factor, the agreed and disagreed proportion is 0.96 and 0.04 respectively, implying that 96% of the experts agree that “poor communication” is a RL risk factor while 4% disagree. According to the result generated by SPSS for the binomial test, the exact significance for communication is 0.000. Therefore, poor communication is a significant risk factor in RL. The results in Table 6 note general agreement for all the risk factors, with the exception of “credit uncertainty”, which has 0.43 agreement versus 0.57 disagreement, with an exact significance of 0.678, meaning it is eliminated from risk factors. This results in 41 remaining significant risk factors. The 22 experts mostly agreed on the proposed model, with a confidence level of 0.95, and the null hypothesis (Eqn 1) is rejected.

<< INSERT TABLE 6 ABOUT HERE >>

<< INSERT TABLE 7 ABOUT HERE >>

4.2 Clustering of RL Risk Factors

The results of the RL risk factors are presented in Figure 5. The 41 accepted risk factors are clustered into three categories, comprising 21, 14, and 6 RL risk factors, respectively. The description of each cluster is presented in the next section.

<< INSERT FIGURE 5 ABOUT HERE >>

To validate the clusters, a one-way ANOVA test is employed and the results are shown in Table 8. Table 9 illustrates the *p-value* of the risk clusters. The standard deviation measures the variability of the scores in each cluster. The 95% confidence interval for the mean displays the upper bound and lower bound that includes the population mean with 95% reliability. Finally, the maximum and minimum values show the highest and lowest values for each cluster.

<< INSERT TABLE 8 ABOUT HERE >>

One-way analysis was applied to identify the significance among the clusters, rounded down to three decimal places (see Table 9). The results indicate that the clusters are significantly different ($p < 0.05$).

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5 Discussion

This study has identified a comprehensive list of risk factors of RL. When closely examined, they can be classified broadly into: Strategic, Tactical, and Operational clusters. Strategic risk factor cluster consists of 21 factors that affect the longer-term strategic operation of an organization. They relate to the more information-centric aspects and those that directly influence the decision-making of the top management. The tactical risk factor cluster comprises 14 factors that affect the medium-term tactical operation of an organisation. They are mostly related to the inventory and supply management issues. The operational cluster consists of six factors that directly affect day-to-day operations. Any disruption as a result of such risk exposures would have an immediate and direct impact on operations, resulting in failure to meet customer demands. Proposed labels are based on the nature of risk factors in each cluster. Due to lack of study in RLRM, recommended clusters are used as a basis to establish a framework in RLRM and future studies in related fields.

As reviewed earlier in the literature, the last step in risk management is risk evaluation. Since, risk identification and risk classification are discussed in this paper, the next logical step is to consider strategies to mitigate the identified risks (Ho et al., 2015; Juttner et al., 2003; Lavastre et al., 2012). Researchers believe that risks are not always negative but may also have positive consequences on organisations' performance. Yet, identification and proposing mitigation strategies are essential to make legitimate managerial decisions to reduce the likelihood of disruptions. Findings of Gouda and Saranga (2018) reflect that mitigation strategies do not always reduce actual supply chain risks but they could be effective if they are used with sustainability efforts particularly in emerging markets. Since RL is known as one of the sustainable recovery methods, RLRM provides a golden opportunity to diminish the negative impact of risk factors on RL organisations' performance.

However, with 41 identified risk factors, it can be costly to address every one of them. A solution would be to tackle the risk factors with the greatest potential impact on performance. This section proposes a strategic framework to tackle the top three risk factors in each cluster. Since various types of risk mitigation have been developed in SCRM to improve performance, this research argues that they are also relevant to RL.

Cluster 1 - Strategic. The top three risk factors in this cluster are: inventory (C30), production planning (C37), and supplier risk (C8) (see Figure 6). One way to reduce inventory risk is to determine the optimal order quantity, as well as safety stock level (Manuj and Mentzer, 2008).

While the SCRM literature does not specify any appropriate mitigation strategy for tackling production planning risk, a qualified information system and developing coordination mechanisms within the upstream and downstream of the supply chain could be an effective tactic, based upon the potential causes of the risk. Supply risk may lead to inventory risk, risk of delay, purchase risk, and capacity risk. One of the strategies researchers agreed on is adding inventory as a strategy for decreasing supply risk, although they note that this might have ramifications such as spoilage of products, obsolescence, holding cost, and transportation cost growth (Chang et al., 2015; Christopher and Lee, 2004; Olson and Wu, 2010; Zsidisin and Wagner, 2010). Hence, this strategy should only be used after due consideration. Another strategy is to have alternative suppliers to cope with supply risk or to maintain multiple suppliers in order to hedge risks (Olson and Wu, 2010; Zsidisin and Wagner, 2010) although this could cause an increase in capacity risk (Giunipero and Eltantawy, 2004; Ketikidis et al., 2006; Zsidisin, 2003).

<< INSERT FIGURE 6 ABOUT HERE >>

Cluster 2 - Tactical. The top three risk factors in this cluster are: purchase (C38), long distance (C10), and labour instability (C15) (see Figure 7). Purchase risk is the result of poor co-ordination between partners and untimely information exchange, while long distance risk relates to geographical differences resulting in long purchasing ordering time and material shortage. Purchase risk can be addressed using a tightly integrated communication system that enables information to flow seamlessly to the right supply chain entity at the right time (Buscher and Wels, 2010; Hajmohammad and Vachon, 2016; Li et al., 2015; Olson and

Swenseth, 2014). Using multiple suppliers and establishing strong partnerships are potential strategies to overcome the long-distance risk. Labour instability could be resolved with long term contract between employers and employees to assure job security for a long term period Blos et al., 2009; Chang et al., 2015; Giunipero and Eltantawy, 2004; Kırılmaz and Erol, 2017; Xie et al., 2011).

<< INSERT FIGURE 7 ABOUT HERE >>

Cluster 3 - Operational. The top three risk factors in this cluster are: financial instability (C14), security (C35), and customer (C36) (see Figure 8). Financial instability includes various risks such as price and cost, exchange rate, and the financial strength of supply chain partners (Tang and Nurmaya Musa, 2011). It can have diverse effects on RL, for instance a high level of financial uncertainty would lead to lower investments by stakeholders in the RL industry. One strategy for mitigating this is to increase coordination between the different parties in the supply chain as recommended by Giunipero and Eltantawy (2004).

Ramanathan (2010) highlights that security risk in online procurement is generally higher than offline procurement. Security risk exposure for the customer is the function of price of the product and the description of the product where reducing the risk is dependent on customer behaviour and the quality of procurement services (Ramanathan, 2010). A robust information management system that provides transparency to customers would help to reduce security risk. One strategy to mitigate customer risk is to manage demand through marketing strategies such as promotions in order to control customer tastes (Diabat et al., 2012; Olson and Swenseth, 2014).

<< INSERT FIGURE 8 ABOUT HERE >>

6 Research Implications

While there are many published papers that seek to identify and examine risk management practices in the SCM context (Aqlan and Lam, 2015; Ho et al., 2015), there are few studies of RLRM. Indeed, some studies in RL have urged for more research related to uncertainty and risk assessment to be carried out (Huscroft et al., 2013; Lambert et al., 2011). This study has therefore contributed to theory by identifying the critical risk factors in RLRM via cross-fertilizing the relevant supply chain risks as a basis to enrich the understanding of RL risk factors. This provides a foundation for subsequent theoretical development work, such as enabling predictive analytics on the impact of the various risk factors on organizational performance in terms of business and operational objectives, as well as the development of a process framework that provides prescriptions on risk identification, classification, and evaluation for effective risk management (Abdel-Basset et al., 2019; Gaudenzi and Borghesi, 2006; Khan and Burnes, 2007; Rao and Goldsby, 2009). The 41 risk factors presented in this paper may assist researchers in developing knowledge on RL risk factors. As the types of risk might vary depending on the application or industry context, further research could develop the means to identify risk contextually. Quantifying the impacts of risk factors on organisational or operational performance can advance knowledge in this domain. Likewise, the successful application of the SOM clustering method in RLRM may boost and encourage its application in other risk management domains.

Along with theoretical implications of this research, managerial implications should be discussed as well. The high costs involved in managing risk deter managers from committing the resources and may result in a willingness to risk facing the consequences. It is almost impossible for effective risk management to take place without sufficient support from management. This research identifies the top three risk factors in each cluster, which will allow managers to focus on the most important risk factors, thereby increasing the probability of buy-in from top management, as well as committing reduced resources while achieving the highest possible gains. The proposed strategic framework suggests certain risk mitigation strategies, and provides decision support for managers. Proposed mitigation strategies are applied in SCRM and with some considerations are recommended for the RL risk factors. Managers of RL companies may apply these strategies in line with companies' strategies for risk mitigation. Minimum cost of risk mitigation in terms of application and prospective consequences on companies' performances have always been a priority for top management. Adopting the right strategy very much depends on RL companies' status quo in the market and their financial stability. Hence, applied SCRM risk mitigation strategies could be a sign for making the right decision at the right time with the right cost.

7 Conclusion

RL gains much attention in recent decades due to its relevance to environmental protection, reduction in energy consumption, efficient resource utilisation, and cost reduction. However, managing RL operations seems risky for most companies. Risk management helps to identify, evaluate, and control negative and positive risks. This research seeks to identify risk factors in RL using both literature of SCRM and interviews with experts in the related field. Identified risks were filtered based on the experts' opinion and 41 risk factors finalised as the basis for RLRM. Through the use of the SOM approach the 41 factors are organized by similar attributes into three clusters; strategic, operational, and tactical, thus enabling the adoption of mitigation strategies for risks in the same clusters. Mitigation strategies are adopted from SCRM risk mitigation strategies for the same factors and recommended for the top three and most important risk factors in RL clusters. We argue that due to the nature of this study being exploratory and the first of its kind in the RL literature, consulting a group of experts to identify and define the relevant risk factors is appropriate. Future research can validate the factors through administering surveys to a larger sample population and employing a more parsimonious statistical technique to investigate the underlying causal relationships with a certain dependent performance of interest.

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