A Decision-Focused Knowledge Management Framework to Support Collaborative Decision Making for Lean Supply Chain Management

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5 authors, including:

Shaofeng Liu
University of Plymouth

Mike Leat
University of Plymouth

Jonathan Moizer
University of Plymouth

Phil Megicks
University of Southampton

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Shaofeng Liu [a], Mike Leat [a], Jonathan Moizer [a], Phil Megicks [a] & Dulekha Kasturiratne [a]
[a] School of Management, University of Plymouth, Plymouth, Devon, UK

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Shaofeng Liu*, Mike Leat, Jonathan Moizer, Phil Megicks and Dulekha Kasturiratne

School of Management, University of Plymouth, Plymouth, Devon, UK

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Lean supply chain management is a relatively new concept resulting from the integration of lean philosophy into supply chain management. Decision making in a lean supply chain context is challenging because of the complexity, dynamics, and uncertainty inherent to both supply networks and the types of waste (defined as any processes, including use of resources, which do not add value to customers). Efficient knowledge management has been identified as one of the key requirements to achieve integrated support for lean supply chain decisions. This paper proposes a decision-focused knowledge framework including a multi-layer knowledge model (to capture the know-why and know-with together with the know-what and know-how), a knowledge matrix for knowledge elicitation, and a decision tree for the design of the knowledge base. A knowledge system for lean supply chain management (KSLSCM) has been developed using artificial intelligence system shells VisiRule and Flex. The KSLSCM has five core components: a supply chain decision network manager, a waste elimination knowledge base, a knowledge refinement module, an inference engine, and a decision justifier. The knowledge framework and the KSLSCM have been evaluated through an industrial decision case. It has been demonstrated through the KSLSCM that the decision-focused knowledge framework can provide efficient and effective support for collaborative decision making in supply chain waste elimination.

Keywords: decision-focused knowledge framework; lean supply chain management; collaborative decision making; knowledge-based decision support system; multi-layer knowledge model; VisiRule; Flex

1. Introduction

Over the last few decades, many companies have adopted the philosophy and principles of lean manufacturing in their operations in order to continuously reduce or eliminate waste. However, no company is a completely isolated island, and the improvements attained from adopting a lean philosophy and its associated practices will only have limited benefits if not extended beyond the four walls of an organisation (Zsidisin 2009). Since the 1980s, manufacturing companies have experienced a paradigm shift from a world consisting of companies competing against each other to that of supply chains competing to meet the ever-more stringent demands of customers. Hence, the integration of lean philosophy and practices into supply chain management (SCM) resulted in the emergence of the new concept of lean SCM in the 1990s (Bruce *et al.* 2004).

The extension of lean philosophy from a single company to the scope of a supply chain, however, has presented great challenges to management decision making. In the organisational decision-making context, decision makers are relatively well equipped with information and knowledge about where the wastes normally occur and how they could be reduced or eliminated. When they are put in the context of a long and more complex supply chain environment, decision situations become much fuzzier to decision makers and they cannot easily see through the complexity and uncertainty of the situations to find optimal solutions for lean decision problems. No decision maker can have all the necessary knowledge about the processes or core resources used in the whole supply chain, and it becomes a lot more difficult to obtain access to and re-use the necessary knowledge that is not created by oneself to make efficient and effective decisions on waste reduction and elimination. Furthermore, in a supply chain, decision makers at different stages of the supply network may have very different decision preferences and priorities. As a result, it is difficult to achieve integrated lean management throughout a supply chain.

It is believed that one key to achieving systematic waste reduction and elimination lies in integrated supply chain decision making. Through integrated supply chain decision making, decision makers in different organisations can

*Corresponding author. Email: shaofeng.liu@plymouth.ac.uk

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synchronise their decisions towards mutually defined goals, that is to say the goals of the supply chain rather than local organisational goals (Manuj and Sahin 2011). Due to the nature of the supply chain decision making in terms of its complexity, dynamics, and uncertainty, waste elimination decision making at the supply chain level is challenging, which has motivated broad research interests in identifying decision support requirements in recent years (Guerra-Zubiaga and Young 2008).

This paper is concerned with one of the key decision support requirements – knowledge management for integrated supply chain waste elimination. The main objectives of this paper are:

- To devise a decision-focused knowledge framework that can address the multiple facets and complex inter-relationships of waste elimination knowledge in the context of supply chains.
- To develop a knowledge-based decision support system as an efficient tool that can provide both novice and experienced decision makers with the necessary knowledge to reach integrated waste elimination decisions throughout supply chains.

The following section gives a review of the recent work in the area. A decision-focused knowledge framework is proposed in Section 3, followed by the discussion on the development of a knowledge-based decision support system in Section 4. A case study is presented in Section 5 discussing the application of the knowledge system to support lean SCM in decision making, before conclusions are drawn in Section 6.

2. Related work

2.1 *Lean supply chain management*

Lean SCM is the evolution of the lean manufacturing philosophy pioneered by the Toyota Motor Corporation. The lean philosophy seeks to reduce waste. "Waste", in this context, refers to the consumption of resources or activities that do not add value to customers. Waste has been traditionally classified into seven types. They are waste which results from over-production, waiting time, excessive process, excessive inventory, transport, motion, and defects (Liker 2004, Slack *et al*. 2010). Lean philosophy has been widely adopted in many companies' practices, and has led over time to great advancements in efficiency being achieved. One of the most significant milestones is believed to be the extension of lean philosophy beyond a company's scope to the whole supply chain, thus resulting in the emergence of a new concept, namely, lean SCM (Holweg 2007).

Lean SCM has been defined as a supply chain operational and strategic philosophy that utilises Internet-enabling technologies to effect the continuous regeneration of supplier and service partner networks (Hines *et al*. 2004). A lean supply chain is empowered to execute superlative, unique customer-winning value at the lowest cost through the collaborative, real-time synchronisation of product/service transfer, demand priorities, vital marketplace information and logistics delivery capabilities. In recent years the lean SCM principles and practices have been widely explored. For example, Wee and Wu (2009) presented a case study where the Ford Motor Company explored the use of value stream mapping as a tool to effectively support lean SCM. The study focused on the effect on product cost and quality. Different approaches to lean SCM are illustrated through case studies in the textile and clothing industry (see for example, Bruce *et al*. 2004). Lean SCM techniques such as discrete event simulation have also been explored in their capacity to help mitigate programmatic cost and schedule risk in the aerospace industry (Hallam 2010).

A common limitation of previous research on lean SCM is that there has been a lack of integrated management approaches to address the problem of supply chain waste from an holistic perspective. Even though different types of waste emanating from lean production have been clearly defined, there has been little reported on using integrated approaches which are based on the study of complex inter-relationships of different types of waste (Rawabdeh 2005). In particular, there is a clear need to explore how to reduce/eliminate one type of waste (occurring at one stage of the supply chain) without adversely affecting the reduction/elimination of other types of waste (which often occur at other stages of the supply chain) in pursuit of achieving overall supply network performance (Allesian *et al*. 2010).

2.2 *Decision making under supply chain complexity*

Due to the vast amount of data, decision variables, intricate interrelationships among the variables and system constraints, and performance trade-offs, highly complex supply chains present great difficulties for management in arriving at sound business decisions. The managerial effort for effectively designing, planning, implementing, and controlling the supply chains is known as supply chain decision-making complexity (Manuj and Sahin 2011). Decision making under conditions of complexity in support of SCM efficiency is a demanding task because of a number of challenges:

(1) The decisions that need to be made involve all types of flows in a supply chain including material flow (from raw material inputs to finished product outputs), design flow (from concept generation to prototyping and final design), information flow (information to facilitate supply chain co-ordination and integration), and fund flow (supply chain activities have to be financially supported to be sustainable) (Wee and Wu 2009, Cetinkaya *et al.* 2011).
(2) The processes need to engage a wide range of stakeholders with different roles, from material providers, designers, and manufacturers to distributors, product retailers, and end customers. They can be dominant players or weak partners in the supply chain, which will affect how the decisions are reached when there are conflicting interests and priorities in existence. Indeed, decision makers might be positioned in complex social networks which could influence their decision-making behaviours (Capo-Vicedo *et al.* 2011).
(3) Due to the nature of supply chain decision making (in terms of its complexity, dynamics, and diversity), various types of decisions need to be made at different times and in distributed organisations of a supply chain. Hence, different decision-making processes or even multi-processes may be used (Liu *et al.* 2010).
(4) The decision propagation paths within a supply network can be in multiple directions (vertical, horizontal, or hub-and-spoke). Subsequently, management of decision changes in supply chain environments is not easy (Kainuma and Tawara 2006).

The above challenges have motivated broad research interests in SCM decision making in recent years. Many decision technologies and approaches have been developed and utilised for SCM (Hittle and Leonard 2011). Among the existing decision methods, multi-criteria decision making (MCDM), collaborative decision making, and fuzzy linguistic approaches have received considerable attention in support of SCM decisions. MCDM is appropriate for SCM because it can empower decision makers to simultaneously consider various decision criteria and factors (quantitative and qualitative, tangible or intangible), resolve conflicts between them, and arrive at justified trade-offs along the value chains. MCDM variants including the analytic hierarchy process and the analytic network process have been widely used to generate weightings (Saaty and Vargas 2006, Dou and Sarkis 2010), and solution approaches such as goal programming and compromise programming were used to compare decision alternatives (Karpak *et al.* 2001, Kumar *et al.* 2006, Narasimhan *et al.* 2006). Collaborative decision making addresses the issue of convergence towards consensus among supply chain partners. Various collaborative decision models such as multi-preference models, adaptive models, and fusion models have been developed and tested which can reduce the number of rounds to reach convergence based on consensus degrees, proximity measures, and preference relations (Mata *et al.* 2009, Cabrerizo *et al.* 2010, Chuu 2011). Fuzzy linguistic approaches combine the strengths of fuzzy set theory and linguistic assessment (based on linguistic variables). As the values of linguistic variables are not numbers but rather words and sentences in a natural or artificial language, introducing linguistic variables in SCM decision making can be extremely useful because linguistic variables can better describe complex and ill-defined decision situations than conventional quantitative expressions (Chuu 2011). Fuzzy set theory was designed specifically to mathematically represent uncertainty and vagueness and to provide formalised tools for dealing with the imprecision intrinsic to multi-criteria decision problems (Beskese *et al.* 2004, Mehrabad and Anvari 2010). Fuzzy linguistic approaches have therefore been widely explored in SCM decision making to address the complexity and uncertainty of the decision situations (Wu and Pagell 2011).

In terms of SCM application scenarios, a significant body of literature exists about decision making surrounding supplier selection and management (Kumar *et al.* 2006, Xu and Yan 2011). Ho *et al.* (2010) provide a comprehensive review on the topic. Work published on decision making in other SCM areas is also extensive and topics addressed include purchasing and outsourcing (Gunasekaran and Irani 2010), distribution and transportation (Yang *et al.* 2005), upstream and downstream integration (Vachon and Klassen 2006), and reverse logistics (Meade and Sarkis 2002, Bottani and Rizzi 2006). Decision making on lean applications is, however, an under-researched area in SCM, despite its importance in reducing supply chain waste in terms of achieving cost, quality, and speed performance objectives.

2.3 *Knowledge management for decision support in lean SCM*

One of the key decision support requirements for SCM has been identified as knowledge management (Guerra-Zubiaga and Young 2008, Gao *et al.* 2009). Knowledge management itself is a well established and developed area (Malhotra 2001). It has been well acknowledged that efficient knowledge flows and knowledge sharing processes among supply chain partners have three advantages: agility, adaptability, and alignment (Lee 2004). Knowledge management application to SCM has been diverse, including multi-level supply chains formed by small and middle enterprises (SMEs) (Capo-Vicedo *et al.* 2011), manufacturing processes and enterprises (Harding *et al.* 2006, Choudhary *et al.* 2009), and manufacturing capability evaluation (Valente *et al.* 2010). Existing work on knowledge management in SCs can be classified along two dimensions: knowledge life-cycle stages and supply chain scales (Marra *et al.* 2012). On the knowledge life-cycle dimension, existing research has extensively addressed the issue from exploitation (knowledge sharing/transfer) to exploration (knowledge creation and learning). It is believed that both knowledge exploitation and exploration have led to greater collaboration among supply chain partners and better collaborative decision-making performance (Halley *et al.* 2010). In terms of supply chain scale, previous research has taken two main approaches: an entire-supply-chain-focused approach and a buyer–supplier-relationship-focused approach (Hult *et al.* 2006). The entire-supply-chain-focused approach investigates knowledge management in a supply chain context and analyses its impact on SCM decision performance (Fugate *et al.* 2009, Capo-Vicedo *et al.* 2011). The buyer–supplier-relationship-focused approach emphasises knowledge sharing and learning as key success factors for supply chain integration decisions (Samuel *et al.* 2011).

Most of the knowledge management work in SCM has so far however been restricted to the management of know-how and know-what, which has not adequately addressed the issue of knowledge support for supply chain decision making from an holistic perspective (Chen 2010). In particular, there is little research reported on mature knowledge-based tools that can efficiently allow knowledge sharing and re-use to support integrated supply chain waste elimination decisions. Thus, there is a need for greater research leading to a decision-focused knowledge management framework that looks beyond know-how and know-what. Specifically this paper will explore the know-why (principles underlying know-how and know-what for decision justification) to support lean supply chain decision making, and explore the know-with (interrelationships among knowledge components for integration) to enable systematic elimination of supply chain waste. The paper will further discuss the development and application of a knowledge system that can support integrated decision making in lean SCM.

3. A decision-focused knowledge management framework

This section proposes a decision-focused knowledge management framework to address the knowledge support requirement for collaborative decision making in lean SCM. The framework comprises a seven by four knowledge model which illustrates the seven key knowledge elements and four knowledge layers required for lean SCM decisions, a knowledge matrix for the knowledge externalisation process with domain experts, and a decision tree to represent the knowledge structure for the design of a knowledge base.

3.1 *A 7 × 4 knowledge model*

Figure 1 shows the key structure of the multi-layer knowledge model defined in this paper. The knowledge model consists of four knowledge layers for the elimination of the seven types of supply chain waste.

Know-what: problems or solutions for supply chain waste elimination are described using facts. It is also referred to as declarative knowledge (Turban *et al.* 2011). The know-what of supply chain waste elimination is important and needs to be stored in a knowledge base, because the facts can help decide when a rule can be fired and a programme can be executed.

Know-how: how to reach a supply chain waste elimination solution in a given situation. It is sometimes referred to as procedural knowledge (Siegel *et al.* 2003). Lean supply chain decision making needs to use tacit knowledge, which is difficult to express in words. Such knowledge is nothing but the steps in a procedure. Examples of know-how are rules, strategies, and models. In the knowledge base, know-how in the format of rules is responsible for taking actions based on the facts, that is to say the know-what.

Know-why: the principles underlying know-how and know-what for decision justification in supply chain waste elimination. Having access to domain experts' knowledge for decision consultation not only helps improve the speed, accuracy, and consistency of decisions, but also provides the ability to back decisions up (Dhar and

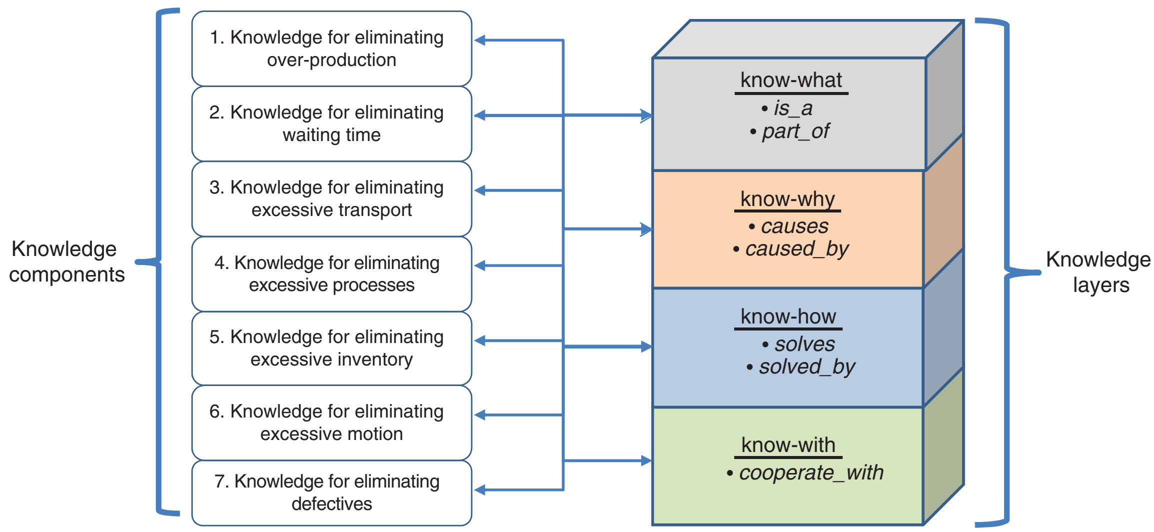

Figure 1. Waste elimination knowledge model.

Stein 1997). Experts can provide justifications for a conclusion, hypothesis, a test, or a recommendation with regard to supply chain waste elimination. In addition, experts can also question the validity of existing facts and bring hypotheticals into the picture of integrated SCM. Investigating know-why for lean SCM waste elimination decisions has two main advantages: explanations and hypothetical reasoning. The system built upon the know-why will be able to reason about how changes affect an existing solution and provide explanations for its decisions, which can add significant comfort for the system users, that is to say supply chain managers as decision makers in the value system.

Know-with: interrelationships among knowledge components for integration. Defining the relational knowledge will help address how to reduce one type of waste without negatively affecting other types of waste in the supply chain. Furthermore, exploring the know-with facet of knowledge will equip decision makers with the knowledge in a supply chain decision network to understand the multi-directional impacts and effects of solutions to different types of waste, to resolve conflicting interests and decision preferences, and to better support orchestrated supply chain decision making (Liu *et al.* 2011).

In the literature, the meaning of the seven types of waste in single company scope has been well defined (Slack *et al.* 2010). However, to the best knowledge of the authors of this paper, there have not been definitions for waste in the supply chain context. Therefore, this section defines meanings for the seven types of waste within the SCM scope. This scope consists of recognising waste at two levels – the micro level and the macro level. The micro level deals with intra-organisational waste and the macro level deals with inter-organisational waste. The micro level can adapt the definitions from the lean manufacturing philosophy, as shown in column 2 of Table 1, while macro level waste has been defined in this paper, as shown in column 3 of Table 1.

3.2 *Knowledge matrix for knowledge elicitation*

An empirical study has been undertaken with respect to supply chain waste elimination and lean SCM decision making. The main focus is on the management practices on integrated supply chain waste elimination including what the main causes for supply chain waste are, how the waste is identified, measured and dealt with, and why particular solutions are employed to eliminate the waste. In order to capture the empirical knowledge of supply chain waste elimination from multiple perspectives as outlined in the knowledge model, a knowledge matrix has been developed, so that a systematic body of knowledge can be obtained for the development of a knowledge base at a later stage. The main research method used for the knowledge elicitation was in-depth, one-on-one interviews with domain experts to collect primary data in SCM. The interviews were semi-structured in nature, with a predefined list of questions but allowing the interviewees to freely give answers and expand on the initial questions. In-depth interview is deemed an appropriate methodological vehicle given the goal of obtaining richness in data through insightful discussion with supply chain managers regarding their waste elimination strategies and practices

Table 1. Definitions of the seven types of waste at micro and macro levels.

Types of waste	Definition at micro level	Definition at macro level
Over-production	Producing more than is immediately needed by the next process in the operation	Producing more than is immediately needed by the downstream operations/consumers/customers in the supply chain
Waiting time	Amount of time waiting for items from previous process in the operation	Amount of time waiting for items from upstream partners/operations/suppliers
Unnecessary transport	Moving items around the operation unnecessarily	Moving things around supply chain stages and partners unnecessarily
Excessive process	Non-value adding processes resulting from poor component design and poor maintenance	Non-value adding operations resulting from poor supply network design
Excessive inventory	Excessive inventory between processes in the operation	Excessive inventory between up-stream and down-stream operations in the supply chain
Motion	An operator or a machine looks busy but no value is added	People and vehicles look busy running between partners/companies but no value is added
Defect	Items produced are below quality standards and need rework or scraping	Items provided by suppliers/upstream operations have serious problems and need to be returned

(Saunders *et al.* 2009). All interviews were audio recorded so that accurate information can be gained for transcription and that direct quotations could also be used for later analysis.

Some examples have been populated for the knowledge matrix showing the macro-level supply chain waste elimination, as shown in Table 2, based on the theoretical and empirical study of supply chains of the electronics manufacturing industry. Knowledge was elicited from the Dell laptop supply network which is responsible for material purchasing, parts manufacturing, laptop assembly, and delivering to customers. The data collected from human experts were consolidated by data from other sources including textbooks, articles, multimedia documents, databases, special research reports and the information available on the Web (Boyer and Verma 2009, Gebus and Leviska 2009). Once the tacit knowledge residing within domain experts has been collected and populated in the matrix, the knowledge is externalised and becomes explicit, and hence is ready to be transferred into a knowledge base for sharing and re-use.

3.3 *A decision tree for the knowledge base design*

The key element of a knowledge-based system is its knowledge base. For many decades rules have served as a fundamental knowledge representation scheme in artificial intelligence (AI). A rule-based approach is advantageous when experts are available and able to specify with a high degree of confidence what they do in specific situations, and why (Turban *et al.* 2011). The task for model and system developers is to extract as much knowledge as possible and turn this knowledge into rules. However, these rules must cover the problem area comprehensively so that there are no inappropriate holes in its knowledge base (Akerkar and Sajja 2010).

Based on the above consideration, the lean SCM knowledge base must construct rule sets comprehensively covering knowledge on all identified main types of waste in supply chains. The overall design of the logic and flow in the knowledge base is shown in the decision tree as illustrated in Figure 2. A decision tree is preferred to an inference net for the design of the knowledge-based system in this paper because the domain experts interviewed could articulate, and without much trial and error, the sequence of steps involved in reaching a supply chain waste elimination conclusion (Siegel *et al.* 2003).

As can be seen from Figure 2, the supply chain waste elimination decision tree has seven parallel branches corresponding to the different types of waste. Within each branch, four knowledge layers are sequentially structured from the know-what through know-why and know-how to know-with. The seven branches merge at the end of the process, that is a step to check the co-operability of different knowledge components. If any conflicts are found, then further actions need to resolve the conflicting issues. New rules may be added at this stage to reflect the knowledge about how a conflict can be or is reconciled.

Table 2. Knowledge matrix populated with examples of macro-level waste elimination knowledge.

	Know-what	Know-why	Know-how	Know-with
Over-production elimination	Over production is a type of waste that produces more than is immediately needed by the down-stream operations in the supply chain	This type of waste is caused by inaccurate forecast of demand and by lack of information sharing between partners	Implement information integration systems such as ERP, better forecasting, and communication	Need to co-operate with process and inventory waste elimination knowledge
Waiting time waste elimination	Waiting time is a type of waste where downstream operations have to wait for materials/parts from up-stream partners	This type of waste is caused by the unavailability of transport; the consequence is longer lead time	Reduce work-in-process (WIP) time, reduce transport	Need to co-operate with transport and process waste elimination knowledge
Transport waste elimination	Transport is a type of waste where products are moved around partners unnecessarily	This type of waste is caused by long distances between production facilities, warehouses, and retail locations	Optimise the locations for production facilities, warehouses, and retailers	Need to co-operate with waiting time waste elimination knowledge
Process waste elimination	This type of waste occurs when nonessential operations designed in the supply chain	Caused by poor supply network design (e.g. including excessive processes in the network)	Identify approaches to reducing number of stages in the supply chain	Co-operate with transport and waiting time elimination
Inventory waste elimination	Extra inventory is a type of waste	Causes extra storage and handling requirements, increases lead time, decreases supply chain's flexibility, and may cause defects	Implement JIT	Co-operate with over-production and defect waste elimination
Motion waste elimination	This types of waste is the inefficient linkage between partners	Motion waste is caused by poor work design and poor coordination between partners	Improve work design and improve supply chain co-ordination	Co-operate with process waste elimination
Defect waste elimination	This is a type of waste when items supplied by suppliers or produced for consumers do not meet quality specifications	Is caused by incompetent purchasing, incompetent resources, and poor quality materials	Implement quality approaches (such as SPC, TQM, Six Sigma)	Co-operate with knowledge of eliminating all other types of waste

4. Development of the lean SCM knowledge system

Knowledge management has been perceived as an optional sub-system for a decision support system (DSS) (Turban *et al*. 2011). However, modern complex DSS may require an additional component that provides expertise to the decision makers. A DSS which includes such a component becomes a knowledge-based DSS (Akerkar and Sajja 2010). A knowledge-based DSS acts as a consultant as it advises and guides non-experts. The knowledge system for lean SCM (KSLSCM) for integrated waste elimination proposed in this paper is a knowledge-based DSS in nature, which provides supply chain managers and production engineers with both suggestions for solutions to eliminate production and supply chain waste (through the know-how and know-with built in the system) and explanations about the solutions (through the know-what and know-why). Three main approaches to the development of modern DSS providing interpretation of knowledge include rule-based reasoning, case-based reasoning, and a hybrid approach (combination of both) (Turban *et al*. 2011). The KSLSCM utilises rule-based reasoning for knowledge capture and interpretation.

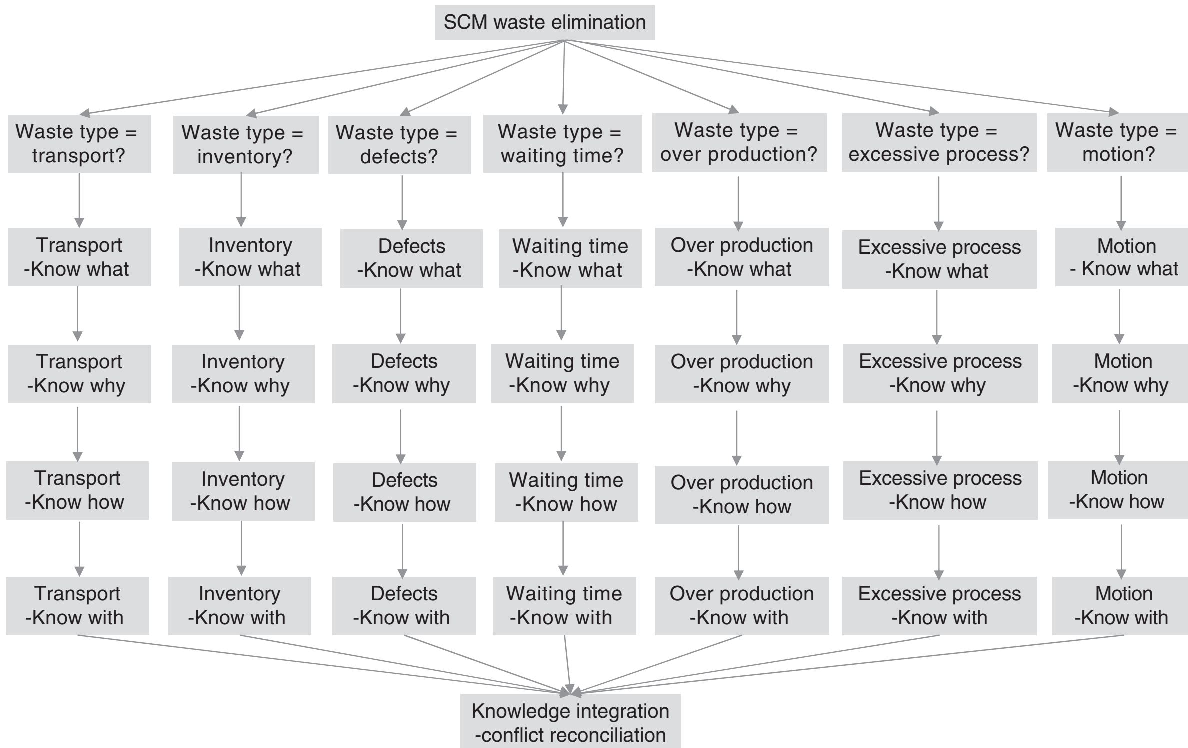

Figure 2. Decision tree for the lean supply chain waste elimination knowledge base.

Based on the understanding of the knowledge support requirement for lean SCM, KSLSCM has been developed to demonstrate the usefulness of the decision-focused knowledge framework in supporting collaborative decision making.

4.1 *Architecture of the KSLSCM*

This paper proposes an architecture for the knowledge system KSLSCM which comprises five key software components: a supply chain decision network manager, a waste elimination knowledge base, a knowledge refinement module, an inference engine, and a decision justifier. The user interface is provided by the adopted AI system shell and therefore is not considered as a key component for the system architecture design. Main functions of the modules are described as below.

Supply chain decision network manager: this component is designed to manage the network configuration of decision nodes (representing different decision makers) in the supply chain, decision propagation paths, and decision settling policy in case conflicting preferences and interests exist between different decision makers.

Waste elimination knowledge base: the knowledge base includes domain experts' knowledge on supply chain waste elimination with four sets of rules to represent the know-what, know-how, know-why, and know-with. A fifth set of rules, namely meta-rules (rules about how to process the relationships across the other four rule sets), has also been defined.

Knowledge refinement module: this module simulates human experts to analyse their knowledge and its effectiveness, learn from it, and improve on it for future decision consultations. The critical component of the knowledge refinement module is a self-learning mechanism that allows it to adjust its knowledge base and its processing of knowledge based on the evaluation of its recent past performance. From this viewpoint, the knowledge refinement module is an intelligent component.

Inference engine: the inference engine is the brain of the KSLSCM system. Specifically, the inference engine has the control structure governing how the knowledge rules should be interpreted and fired (activated) to reach appropriate supply chain waste elimination decisions.

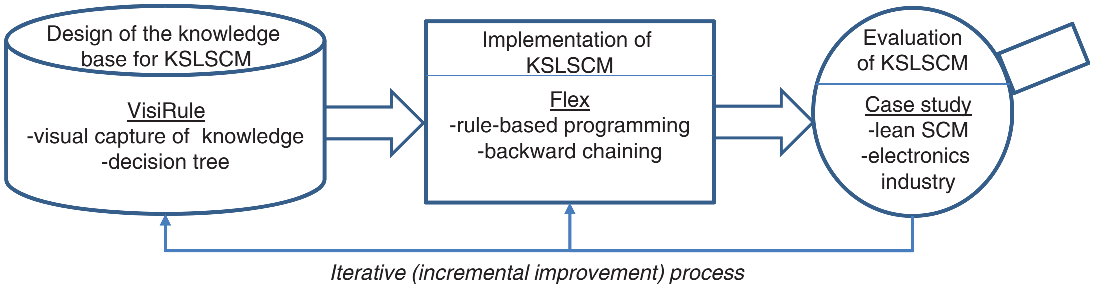

Figure 3. KSLSCM development process within AI environment.

Decision justifier: the decision justifier provides clear explanations in supply chain waste elimination knowledge re-use and decision making through its ability to trace responsibility for conclusions to their sources. It can trace such responsibility and explain the KSLSCM behaviour by interactively answering questions such as: how was a certain conclusion reached? why was a certain alternative rejected? and what is the complete plan of decisions to be made in reaching the conclusions?

4.2 *KSLSCM development environment and process*

Development of a quality knowledge-based DSS needs two important mechanisms: a process that provides disciplines and an integrated AI environment which can provide end users with a platform to readily develop their own applications. Knowledge-based DSS may be developed using many different tools, including algorithmic programming languages (such as Basic, C, C++), AI languages (such as Prolog and Lisp), and expert system shells (Dhar and Stein 1997). The KSLSCM has been developed using the LPA Prolog system tools, specifically VisiRule and Flex (Spenser 2007). There are three main reasons for choosing the LPA Prolog system tools: (1) LPA Prolog system is a fully-integrated logic programming environment; (2) the embedded toolkit VisiRule allows to create visual knowledge models using flowcharts and a backward chaining inference engine; (3) the embedded toolkit Flex supports rule-based programming, frame-based reasoning with inheritance, and contains its own knowledge specification language. The combination of VisiRule and Flex provides a powerful development platform with a logic programming function and visual presentation.

The iterative process for the KSLSCM development consists of three key steps: the design of the knowledge base, implementation of the system, and evaluation of the system. Figure 3 illustrates the process with support of the chosen AI tools. The design of the knowledge base has been discussed in Section 3.3 with a decision tree. Evaluation of the system will be discussed in detail in Section 5 with a decision case.

5. Case study

This section discusses a case study from the electronics industry, specifically the Dell laptop global supply network. The reasons to have chosen the Dell laptop supply network were based on its key characterises – with typical challenges presented by supply chain decision situations as discussed in Section 2.2. Laptops are highly complex and innovative products which are produced by global supply networks with discrete processes under a rapidly evolving environment. Producing laptops requires abundant data but often only partial knowledge is scattered all along the supply chains. Compared with mature lean methods developed in the automotive and aerospace industries, existing work on waste reduction and elimination in the electronics industry is less mature but warrants further research (Lee-Mortimer 2006, Browning and Heath 2009, Wee and Wu 2009).

5.1 *The case of a laptop supply network*

For evaluation purposes, the KSLSCM demonstration system utilises an industrial case study. In the case example, supply chain managers need to consider elimination of defectives through quality control of suppliers. In the electronics industry, many companies such as Dell use hundreds of suppliers in their global supply networks (Barnes 2008), as shown in Figure 4. Due to the sheer number and disparate natures of the suppliers, quality

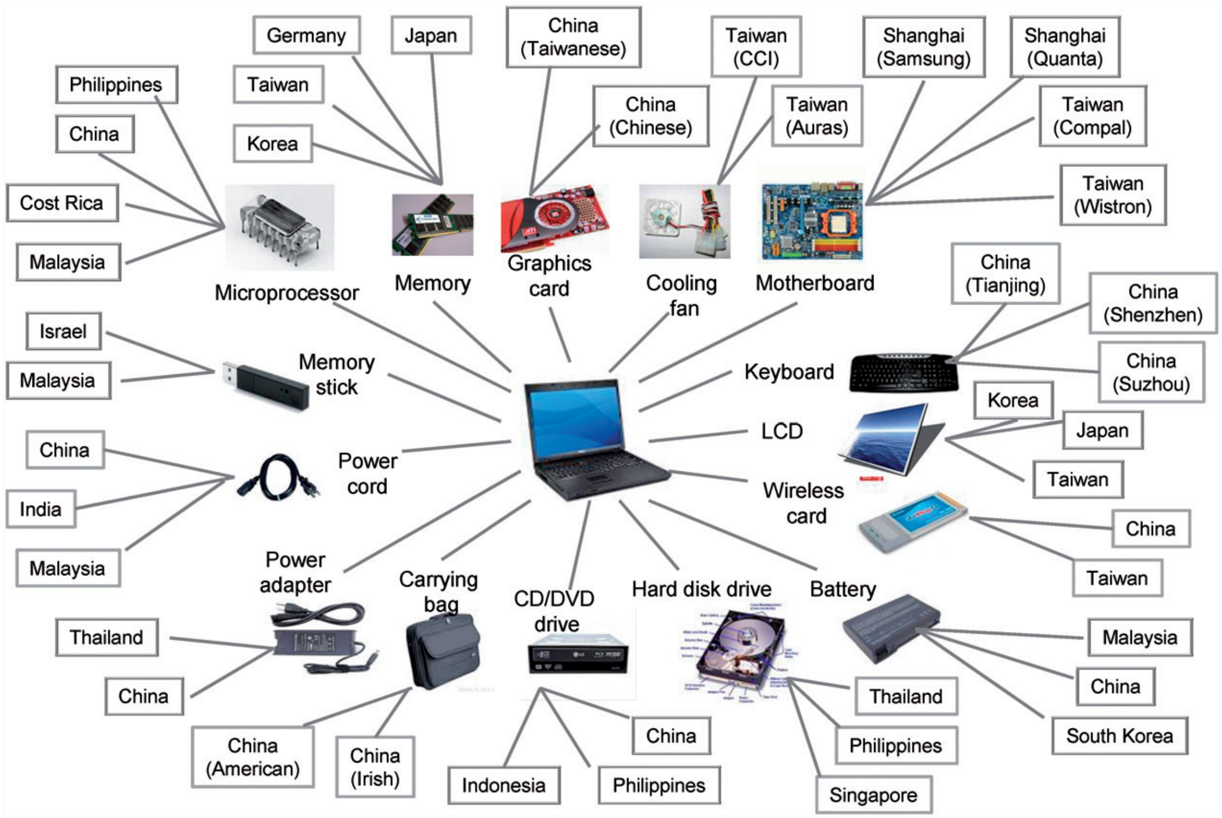

Figure 4. Immediate suppliers in Dell's global laptop supply network (Barnes 2008).

standards and internal quality control processes used by the suppliers can vary significantly. Many defects of final products such as laptops result from the poor quality of the sub-assemblies and components (such as microprocessors, memories, graphics cards, and so on) provided by their suppliers. Therefore, undertaking strict quality control is essential in eliminating defects to ensure the final product quality.

Many quality control approaches have been developed and adopted in operations and supply chain management, most notably statistical process control (SPC), total quality management (TQM) and Six Sigma for quality management, and plan-do-check-action (PDCA) and define-measure-analyse-improve-control (DMAIC) for continuous improvement. Specifically in relation to the quality control of suppliers, there are three main approaches widely in use: no-inspection, brute-force approach, and threshold approach (Dhar and Stein 1997, Slack *et al*. 2010). The no-inspection approach relies on the suppliers for all quality control and just accepts all orders without checking them. The brute-force approach checks every shipment for damage and accuracy. The threshold approach involves checking orders that are larger than a certain cash threshold value. Smaller orders are passed without inspection. Needless to say, different approaches have different levels of complexity when it comes to implementation and often result in different costs, order processing speeds, and inventory levels. Therefore, the decision on the right quality control approach to reduce/eliminate defect waste often needs support from expert knowledge for the right judgement.

5.2 *Application of the knowledge system to support decision making in lean supply chain waste elimination*

In the demonstration system, the knowledge represented by the logic rules shown in Figure 5 is a branch of the decision tree as defined in the previous section. The rules designed within VisiRule are transformed into programming codes in Flex, as shown in window (a) in Figure 6. These coded rules are then compiled within the AI environment, as illustrated in window (b). KSLSCM users can interact with the system through the graphical user interface (as in window (c)) answering prompts by a simple point and click action following the defined logic.

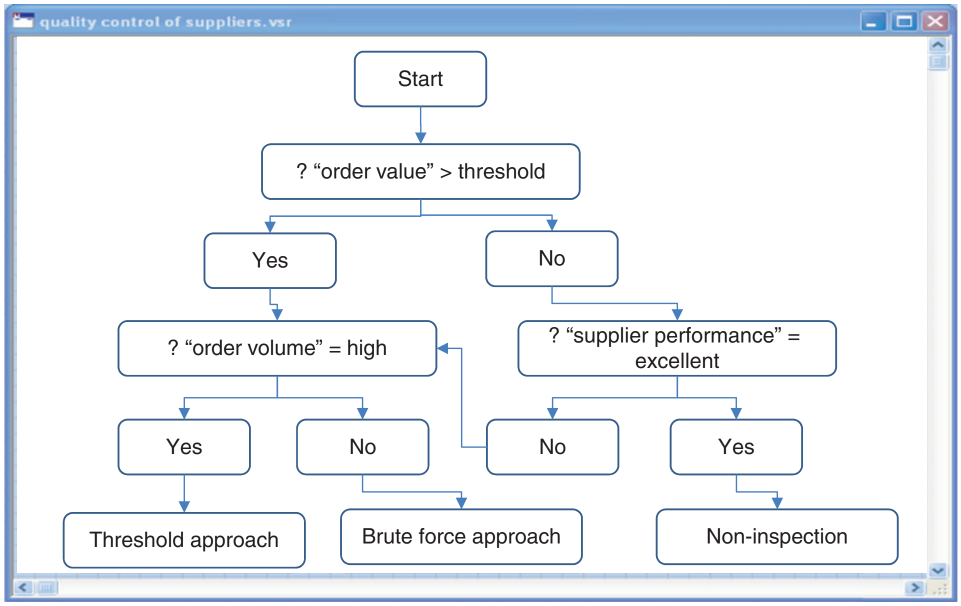

Figure 5. Logic flow-chart for demonstrating quality control of suppliers.

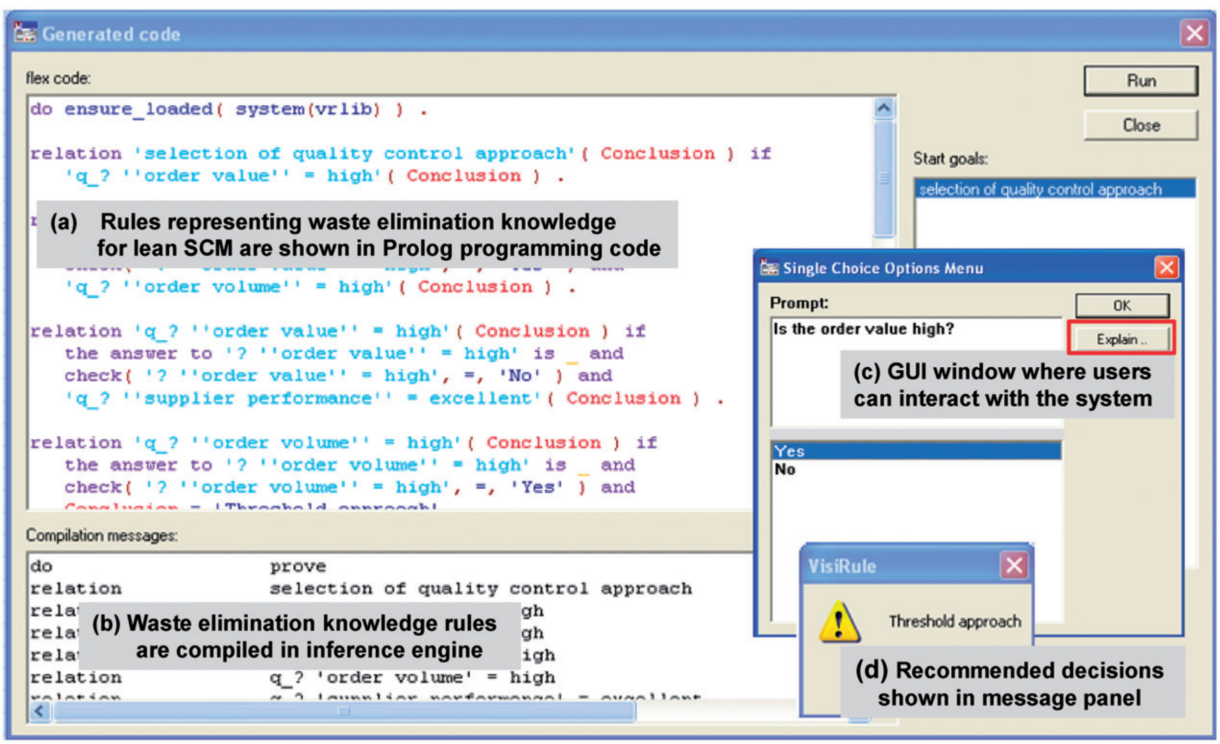

Figure 6. A screenshot of the KSLSCM supporting decision making in lean supply chain waste elimination.

The final solution suggested by the system (that is to say the threshold approach in this case) will be displayed to users in easy to understand messages, as illustrated in window (d).

The “explanation” button in the GUI window as seen in Figure 6(c) is important to a knowledge-based decision support system, because having access to expert knowledge is valuable as it improves the accuracy of decisions as well as validates them. The explanation function allows the KSLSCM users to seek justification for supply chain waste elimination solutions. The ability to provide explanations for its decisions can add significant comfort value for the decision makers. However, the provision of explanation in a knowledge-based DSS comes at a cost. Firstly, system developers have to understand the problem area much better than if they were working with a black box approach such as a neural network. They have to extract significant problem-solving context knowledge, that is to say seven types of waste elimination knowledge in the case of KSLSCM. This can take a significant amount of time and effort. Secondly, from a computational point of view, extra overhead is incurred in terms of memory and reasoning machinery, which is sometimes referred to as reason maintenance (Dhar and Stein 1997).

5.3 *Evaluation of the KSLSCM with managers and feedback on the system*

The evaluation of the KSLSCM with managers has been undertaken through evaluation workshops and demonstration activities using the laptop supply network case. The main purpose for the evaluation was to determine the performance of the KSLSCM in supporting managers with decision making on waste elimination in the context of supply chains. Three evaluation workshops were held on industrial sites, where 16 operations and supply chain managers took part in trials of the system. Each participant was given the same decision case and a software KSLSCM user manual. One KSLSCM developer acted as a facilitator to set up the system and sort out unexpected technical problems if occurred. However, the facilitator was instructed not to guide the managers through the software system or influence the managers' judgement on waste elimination problems. Each workshop allocated up to one hour for the participants to play around with the software individually at their own pace. A feedback questionnaire was completed by the participants during the workshop. The system developer then held further discussions with the managers to clarify the answers they provided on the questionnaire and to receive any open comments that were not captured within the questionnaire responses. Two demonstrations were held at two international conferences. During the demonstrations, the system developers ran through the software with live commentaries using the same laptop decision case. Over 20 managers were asked to attend the demonstration and give feedback using the same questionnaire. Eighteen feedback forms were returned. In total, nearly 40 managers participated in the evaluation process, with 34 feedback forms collected from the combined workshops.

The feedback questionnaire consisted of 20 questions designed to collect the managers' opinions on seven key aspects of the KSLSCM performance against a set of user requirements: (a) decision process flow through the supply network; (b) access to waste elimination knowledge base; (c) decision explanations provided by the decision justifier based on the know-why knowledge; (d) interoperability provided by the know-with knowledge (e) reasoning capability provided by the inference engine; (f) system learning provided by the knowledge refinement function; and (g) visualisation of the user interface. For each question in the survey, participants were asked to score the system performance using a number between 1 and 5, with 1 representing very poor, 2 poor, 3 average, 4 good, and 5 very good. Based on the analysis of all feedback collected, the five aspects that participants scored highly were the decision process flow, knowledge base access, decision justification, interoperability, and reasoning capability (with average scores of 4.1 for a, 4.3 for b, 4.7 for c, 4.5 for d, and 4.4 for e, respectively). The aspect that scored lowest was the system learning capability (with an average score of 2.7 for f). The visualisation of the user interface received a very average feedback (3.1 for g). The evaluation feedback has helped the researchers to understand the strengths and weaknesses of the system from the users' perspectives. It has provided clear guidance to the researchers on future work and allowed the system developers to consolidate the KSLSCM.

In terms of the limitations of the software, participants fed back a recommendation that the system should be upgraded onto a web-based platform and implemented with a server–client architecture, so that in the future both the user tests of the software and the feedback surveys can be undertaken remotely without restriction from physical meetings. By evaluating the system online, it would not only save the system developers time and travel expenses, expanding the evaluation with more participants, it would also allow the users to try out the system and give feedback at their earliest convenience.

6. Discussion and conclusions

This paper discussed a knowledge-based decision support system called KSLSCM which can offer supply-network-wide waste elimination advice and suggestions to supply chain managers involved in the collaborative decision-making process to achieve overall lower costs and better quality. The main contributions of the paper are:

- It has proposed a new decision-focused knowledge architecture that captures seven waste elimination knowledge components generated from different stages across supply chains. Each knowledge component is systematically structured in four layers (know-what, know-why, know-how, and know-with). The knowledge architecture has been transformed into a knowledge matrix for knowledge elicitation. Thus, this paper extends existing knowledge management work for decision support from a two-layer architecture which only captures the know-what and know-how (Malhotra 2001, Chen 2010). By capturing the know-why and know-with of the supply chain waste elimination and implementing them into the decision support system KSLSCM, it enables supply chain managers to gain insights into the decision justifications and increase their confidence in reaching better global lean decisions.
- It has discussed the capture of waste elimination knowledge through using the AI toolkit VisiRule, allowing the knowledge objects and relationships to be visualised, which enables transparent update and maintenance of the knowledge objects and their relationships within the knowledge base. Effectively managing the knowledge relationships in the KSLSCM knowledge base is extremely important, because otherwise the adverse effect of reducing one type of waste in the supply chain on another cannot be addressed. Compared with existing research which has addressed the elimination of different types of waste in an isolated manner (Hines *et al*. 2004, Browning and Heath 2009), the VisiRule decision tree designed for the KSLSCM knowledge base provides a conduit for the know-with layer of the knowledge architecture to be practically implemented in the system. Subsequently, KSLSCM can support decision makers in examining the waste elimination issues through taking an entire-supply-chain-focused approach, to help achieve better overall performance.
- It integrates the supply chain waste elimination knowledge model into an AI system shell, Flex, which allows the inference results to be visualised and presented to all decision makers for better collaborative decision making along the supply chains. The inference engine of the KSLSCM has the control structure governing how the knowledge rules should be interpreted and fired (activated during the system execution). By doing so, an articulation mechanism is provided to avoid confusion and misunderstandings of knowledge regarding waste reduction/elimination between different supply chain partners. Existing work has identified the heterogeneity of knowledge and misunderstandings as major barriers to the effectiveness of interoperability within supply chain decision making (Marra *et al*. 2011).

Managerial implications from the work are twofold. Firstly, in the context of supply chain waste elimination decision making, decision makers' judgements can be significantly improved by using a well-developed waste elimination knowledge base. Managers should encourage knowledge exploitation (externalisation, sharing, and reuse) and support investment in the development of knowledge-based DSS within lean SCM systems. The consistency of decision performance is also expected to be improved when knowledge-based systems are utilised (Liu *et al*. 2010). Secondly, managers in lean SCM should think holistically, and be constantly aware that decisions made within one company may have severe knock-on effects on upstream and downstream supply chain partners. Sufficient considerations need to be given to decision propagation path and decision change management along the decision network. Because of the complexity of global supply networks, it is essential that efficient support is provided through decision tools such as the supply chain decision network manager inherent to the KSLSCM.

The limitations of the KSLSCM, based on evaluation feedback, are its implementation platform and its learning capability. The system's learning capability is determined by the self-learning mechanism implemented within the knowledge refinement module. The current version of the KSLSCM has not as yet been developed for running on web-based platforms. Consequently, this constrains its usability and integration with other web decision tools.

Further research will be exploring two key issues:

(1) Consolidation of the knowledge base to include an additional layer of meta rules so that priorities of the supply chain waste elimination knowledge can be specified. For example, the priorities can be given to the most recent knowledge. The meta-rules will be fed into the knowledge refinement module to improve the intelligence of the KSLSCM.
(2) Extension of the KSLSCM to a web-based system to promote knowledge sharing and reuse in the context of global supply chains (Liu and Young 2011). Along with the rapid advancement of Internet and web

technologies, a web-based KSLSCM would also allow it to be wrapped as an embedded system and plugged into Web 2.0/3.0 to allow it to work together with supply chain management tools.

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