Decision Support Systems to Detect Quality Deceptions in Supply Chain Quality Inspections: Design and Experimental Evaluation

Abstract

Supply chain quality inspection (SCQI), which is carried out to measure the product quality based on quality requirements, is a widely-adopted instrument when a buyer purchases products from suppliers. However, when suppliers are deliberately cheating to manipulate the products and falsify the specific testing methods (i.e., quality deception), traditional operation management theories fail to guide the industry SCQI practices, causing tragedies like tainted milk scandals. We propose to address this problem from a perspective of information gathering and knowledge reasoning. We argue that the rationale behind the quality deception in SCQI could be analyzed, predicted, and thus prevented, based on collecting information from supply chains. In this paper, we adopt a Design Science approach to design Decision Support Systems (DSS) that analyze and predict suppliers’ possible production behaviors. Based on the decision supports, buyers can make effective inspection policies to detect quality deception while minimizing inspection costs. In order to illustrate the effectiveness of this approach, we build a prototype and use a laboratory experiment to demonstrate the prototype’s superiority in supporting inspection policy making in supply chains.

Keywords: Supply chain quality inspection, decision support systems, design science

Introduction

In Supply Chain Quality Inspection (SCQI), a supplier offers products to a buyer and the buyer implements inspection policies to inspect the products. The decision making of inspection policies is a tradeoff between inspection costs and accuracy. Excessive inspections can lead to higher costs, whereas
inadequate inspections can lead to significant inspection errors. Therefore, a major objective of SCQI studies is to find an optimum to minimize inspection costs with minimized inspection errors.

Inspection errors can be classified into sampling errors and diagnostic errors (Starbird et al. 2006). Sampling errors occur when the selected samples do not represent the entire products. An inappropriate sampling policy will cause sampling errors. Diagnostic errors occur when the quality characteristics of a sample are incorrectly measured. The analysis of diagnostic errors is related to the domain-specific knowledge of products and inspection technologies. Improper handling of testing policy (i.e., selection of testing methods) may result in significant diagnostic errors. To facilitate the generalization of the inspection models and theories, most existing SCQI studies regard diagnostic errors as mathematical abstractions. That is, they assume that testing methods used in quality inspections are without diagnostic errors or that the probability of diagnostic errors is regarded as a known mathematical function. These mathematical abstractions treat the process of quality inspection as a black box, without capturing the domain-specific knowledge of products and inspection technologies. Therefore, most of current SCQI are indifferent to testing policy (Mandroli et al. 2006).

However, these assumptions do not work in practice when suppliers are deliberately cheating to manipulate the products and falsify the specific testing methods. We regard this type of cheating in SCQI as Quality Deception. Quality deception is a challenging problem especially in the food supply chain, because the suppliers can take advantages of diagnostic limitations and high costs of food inspection technologies. An example can be found in the 2008 tainted milk scandal. Some suppliers for Sanlu, a well-known Chinese dairy manufacturer, diluted milk for profit by adding melamine, in order to dupe those inspections for protein content, affecting some 294,000 infants and killing six (Xin et al. 2008). In this example, the testing method to measure protein content—the Kjeldahl method—was considered to be very theoretically accurate (Wiles et al. 1997). However, significant diagnostic errors occurred using the Kjeldahl method because the suppliers were purposely deceptive and added melamine to fake the protein characteristic. Sarcastically, this is not the first time that people uses melamine to falsify the protein testing. There was another notorious case of melamine contamination in 2007, in which many brands of cat and dog foods in Europe and the U.S. are recalled. In other words, the knowledge of melamine was repeatedly used in quality deception by suppliers with ulterior motives. Although the milk scandal brings about comprehensive reforms to the food safety regime in China and other countries (Chen et al. 2013; Pei et al. 2011), we can still see a list of food quality deception and contamination incidents in the past several years (Thomson et al. 2012). Most of these events are caused by deliberately contaminated to take advantage of ineffective SCQI. For instance, a study in 2012 found that 70% of milk in Delhi is adulterated with detergent, fat and even urea, and diluted with water (Sinha 2012). In 2013 meat adulteration scandal, horsemeat was passed off as beef in Europe (Premanandh 2013).

In such cases, the supplier’s possible cheating behaviors should be considered in the SCQI to prevent the tragedies. Supplier’s decision making of such cheating behaviors is based on a knowledge reasoning process based on the domain-specific knowledge of products and inspection technologies. Therefore, we propose to address this problem from a perspective of information gathering and knowledge reasoning. We argue that the rationale behind the quality deception in SCQI could be analyzed, predicted, and thus prevented, based on information collected in supply chains. In this paper, we adopt a Design Science Research Approach (Hevner et al. 2004) to design Decision Support Systems (DSS) that analyze and predict suppliers’ possible production behaviors. If it is inferred that the supplier is likely to choose some deceiving approach to dupe an inspection technology, then the risk of diagnostic errors will be highlighted. Based on the decision supports, buyers can make effective inspection policies to detect quality deception while minimizing inspection costs. We develop a prototype based on a simulation platform of dairy product transactions, and evaluate its effectiveness in a laboratory experiment.

The organization of this paper is following guidelines and steps for design science research practices (Peffers et al. 2007): In the background section, we identify the research problem from the gap in literature and industry practice, explain the appropriateness of the design science approach in addressing the problem. In Section 3, we define our research objectives and provide the design of DSS for SCQI. In Section 4, a prototype is demonstrated, and we carry out a laboratory experiment to evaluate the effectiveness of this prototype. We conclude with the contributions of this work in the final section.
Background

Supply Chain Quality Inspection

Quality inspection, which is carried out to measure the product quality based on quality requirements, also follows the general objective of Operations Management (OM), i.e., maximizing (quality) performance and minimizing (quality-related) costs. To design an inspection policy, two basic concerns need to be taken into account (Chevalier et al. 1997): (1) at which workstation and which product to be inspected, known as the inspection allocation problem or sampling policy, and (2) what kind of testing method should be used if an inspection activity is needed, which is known as the testing policy.

Most existing analytical models or empirical works in SCQI studies focus on mathematical solutions to optimally allocate inspection resources, and well-established statistical theories have been applied to support effective decision making of sampling policies (Chorafas 2013). Mandrolı et al. (2006) discovered that, in order to get a mathematical solution, most SCQI studies would assume either that the quality testing is perfect (without diagnostic errors) or that there is a known probability of the diagnostic error. This assertion is in line with our observations in many of recent SCQI studies, such as (Khan et al. 2014; Li et al. 2011; Priyan et al. 2014; Wang et al. 2012a). Among those works that consider testing policies, the testing policies are always associated with diagnostic errors following mathematical distributions (Gani et al. 2013; Shiau 2002; Shiau 2003a; Shiau 2003b; Valenzuela et al. 2004). This leads to a gap that most SCQI studies are indifferent to making testing policies to detect quality deceptions. The major reason for this gap is because the decision-making of testing policies is a knowledge reasoning process that relates to the domain-specific knowledge of products and inspection technologies. For instance, milk inspection needs biotechnical knowledge, while electronic knowledge may help to inspect TV sets. There is a lack in SCQI analytical or empirical models for learning and reasoning with these domain-specific knowledge. Thus, the tasks of selection and improvement of testing methods are inclined to be passed to the product domain experts.

Although advantages and disadvantages of various testing methods have been well studied by product domain experts, there is a lack of decision models in current SCQI literature that provide supports for avoiding quality deceptions. Take the milk scandal as an example, the knowledge of melamine has been learnt long ago and domain experts have invented various methods to examine the protein or melamine contamination. However, people are still confused how to select inspection technologies to avoid melamine deceptions while keeping down inspection costs, because there is a lack of factoring the melamine knowledge into the decision-making of SCQI. A promising solution is to design expert systems that capture the knowledge of domain experts via knowledge engineering and make proper decisions with decision models. This research direction has aroused increased interest in recent years. For example, Wang et al. (2012b) develop a new risk assessment approach to perform structured analysis of aggregative food safety risk in the food supply chain by using the concepts of fuzzy set theory and analytical hierarchy process. Luo et al. (2012) developed a real-time food safety management system for receiving operations in distribution centers. Based on RFID techniques, Kumar (2014) devised a responsive and reliable knowledge management framework for product safety and recall supply chain for the focal global manufacturing and distribution enterprise. These successful applications of expert systems in supply chain quality management motivate us to design DSS for investigating the issue of detecting quality deceptions which hasn’t been well studied in the literature.

Overall, there are two reasons to deploy the design science approach to fill these gaps in SCQI literature. First, SCQI is a complex problem-solving process that are related to the domain-specific knowledge of products and inspection technologies. There is a lack of information systems that could learn and reason with the domain-specific SCQI knowledge. Second, how to avoid quality deceptions in SCQI is a decision making process that requires the incorporation of domain-specific knowledge into the trade-off analysis and knowledge reasoning of quality deceptions. In our preliminary work, we have analyzed the requirements for detecting quality deceptions in SCQI (Wang et al. 2010; Yan et al. 2009a; Yan et al. 2010; Yan et al. 2009b). We find that the modeling approach of Belief-Desire-Intention (BDI) is an appropriate approach to model and predict the suppliers’ behavior of quality deceptions. In the next section, we will introduce why we choose BDI modeling to design the DSS for SCQI.

Belief-Desire-Intention Modeling
Our approach is based on BDI modeling, which is a framework for knowledge representation and rational reasoning. A BDI model can be used to characterize a rational actor with certain mental attitudes of belief, desire and intention, representing respectively the informational, motivational, and deliberative states (Fishbein et al. 1975). These mental attitudes determine the actor’s behaviors (Rao et al. 1998). We summarized the characteristics of BDI models (Georgeff et al. 1998; Rao et al. 1995) in the right column of Table 1.

<table>
<thead>
<tr>
<th>Features of SCQI</th>
<th>Characteristics of BDI models</th>
</tr>
</thead>
<tbody>
<tr>
<td>➢ Product domain-specific knowledge is necessary to be incorporated in the evaluation of testing policy.</td>
<td>➢ Founded on knowledge representation of the information environment in a specific domain.</td>
</tr>
<tr>
<td>➢ Information about suppliers or buyers is not accurate but is based on estimation, while the deceiving knowledge appears and changes.</td>
<td>➢ The domain information is dynamic, and can be partial and uncertain.</td>
</tr>
<tr>
<td>➢ Different objectives are held by the suppliers, such as making money, risk concerns, and reputation concerns.</td>
<td>➢ Many different objectives (need not be consistent) can be desired to accomplish.</td>
</tr>
<tr>
<td>➢ Quality inspection is an optimization problem seeking to effectively measure product quality in a cost-minimizing means.</td>
<td>➢ Rational reasoning is included to select an optimal action.</td>
</tr>
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The left column of Table 1 outlines several features of SCQI, which match the characteristics of BDI model quite well. As reported by Xin et al. (2008), “millions of people experiment with new ways to make money without moral self-constraint” in order to evade existing testing methods. Thus, the quality inspection should be embedded in a dynamic environment where knowledge of deceiving approaches are appearing and changing. When new information comes to light, the evaluation results regarding an inspection policy need to be changed. BDI modeling provides an approach to knowledge reasoning under a dynamic knowledge environment in a specific domain. Also, the BDI model provides a mechanism to receive partial and uncertain information. This feature provides a solution to the uncertainty and estimation features of information because of the information asymmetry in supply chains. Further, the supplier’s different objectives can also be modeled by the BDI approach.

**Design of DSS for SCQI**

To address the research challenges summarized in Section 2, we propose to adopt the design science approach to design DSS that supports the knowledge reasoning and trade-off analysis in SCQI. As shown in Figure 1, our research framework follows the guidelines for design science in information systems research (Gregor et al. 2013; Hevner et al. 2004). The SCQI environment provides the problem space in which we are seeking intelligent ways to deal with the quality deceptions. The suppliers may have the intention to deceive in the SCQI by taking advantages of inspection errors, which brings the business need of DSS for SCQI. In the process of design and evaluation, we follow theories supply chain quality management and rational choice theory, adopt the agent-orient and belief-desire-intention modeling techniques to factor in the domain knowledge of SCQI. Methodologies of systems analysis and lab experiment provide guidelines used in the design/evaluation phase.

In this section, we focus on the design of decision support systems for SCQI, which consists of two components: First, a knowledge representation framework is provided to organize and formalize the information collected. Second, we design knowledge reasoning rules and an execution procedure to execute the model to analyze and predict suppliers’ production behaviors.
Detecting Quality Deceptions in Supply Chain Quality Inspections

**Knowledge Representation Framework**

As a rational being, the supplier is driven by its best interests (Bratman 1987), i.e., its desires, to choose an optimal approach to satisfy the quality inspection. Thus, we adopt the theory of rational agent to model suppliers as a rational agent with information of the inspection environment, certain objectives to accomplish, and reasoning capability for actions achieving those objectives. Our knowledge representation framework is adapted from Belief-Desire-Intention (BDI) modeling (Rao et al. 1998). In this section, we will describe our knowledge representation framework.

To capture the domain knowledge in the BDI-model, we adapt the concept of “possible world”, which is widely used in rational agent modeling (Cohen et al. 1990; Rao et al. 1998). A possible world consists of a sequence of states indicating the past, a state indicating the present, and several alternative paths to future states. Each state occurs at a certain time point and can be characterized by a set of logic propositions specifying what holds true at that time point. Each logic proposition is composed of (1) primitive propositions representing knowledge of entities and relationships in the quality inspection domain, and (2) logic operators including propositional operators and temporal operators.

The basic element in our knowledge representation framework is primitive proposition. It is a first-order component to represent entities, the properties of entities in SCQI, and how these entities stand in relation to one another.

**Definition 1. (Primitive Proposition)** A primitive proposition \( \varphi \) is a term or formula written in first-order logic to state facts in SCQI. The primitive propositions assert and represent facts that include entities, as well as the properties and relations of entities in SCQI.
Table 2. Basic concepts and primitive propositions

<table>
<thead>
<tr>
<th>Concept</th>
<th>Primitive proposition</th>
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<tbody>
<tr>
<td>Supply contract</td>
<td>$sc = Contract (su, bu, p, Qr, m)$, where su is the supplier, bu is the buyer, p is the product, Qr is the set of quality requirements, and m is the price to buy the qualified product.</td>
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<tr>
<td>Product</td>
<td>$p = Product (Qa, Ma)$, where Qa is the set of quality attributes ${qa}$, and Ma is the set of measurable attributes.</td>
</tr>
<tr>
<td>Inspection policy</td>
<td>$ip = InspectionPolicy (qr, ma, sp, ic, pr)$, where qr is a quality requirement, i.e., $qr \in Qr$; ma is a measurable attribute, i.e., $ma \in Ma$; sp is a specification set for the measurable attribute; ic is the inspection cost; and pr is the precision of the inspection technology.</td>
</tr>
<tr>
<td>Quality production</td>
<td>$qp = QualityProduction (p, PL, PC, RM, c, EQ)$, where p is the product to be produced, PL is the set of manufacturing plants, PC is the set of production procedures, RM is the set of raw materials, c is the cost of carrying out quality production, and EQ is the set of expected product attributes.</td>
</tr>
<tr>
<td>Quality deception</td>
<td>$qd = DeceptionApproach (p, DM, PL, PC, RM, c, EQ, EA)$, where p is the product to be produced, DM is the set of deception materials, PL is the set of manufacturing plants, PC is the set of production procedures, RM is the set of raw materials, c is the cost of carrying out quality deception, EQ is the set of expected product quality attributes, and EA is the set of expected measurable product attributes.</td>
</tr>
<tr>
<td>Nonproduction</td>
<td>$np = NonProduction (p, c)$, where p is the product to be produced, and c is the cost of carrying out the nonproduction.</td>
</tr>
<tr>
<td>Quality inspection</td>
<td>$qi = QualityInspection(ip, p, MP)$, where ip is the inspection policy, p is the product, and MP is the set of measurement points.</td>
</tr>
<tr>
<td>Supplier’s revenue</td>
<td>$rev = Revenue (sc, qi, c)$, where sc is the supply contract, qi is the quality inspection, and c is the cost of carrying out the actions (including quality production, quality deception, or nonproduction).</td>
</tr>
<tr>
<td>Supplier’s resource</td>
<td>$sr = SupplierResource (RMP, RRM, RPC, RDM)$, where RMP is a set of manufacturing plants, RRM is a set of raw materials, RPC is a set of production procedures, and RDM is a set of deception materials.</td>
</tr>
</tbody>
</table>

Table 2 shows some basic concepts and primitive propositions. As we can see, it is implicitly assumed that proposition is expressing the facts at some particular time. Since the suppliers may not believe such things at some later time, our knowledge representation framework incorporates a temporal component to represent what have been changed over time. A set of modal connectives are incorporated to express the temporal properties. $◊$ means sometimes, and thus $◊φ$ is satisfied now if $φ$ is satisfied either now or at some future moment. Similarly, $□$ means always, and $○$ means next.

In order to express the dynamics of SCQI environments, we assume that the environment may be in any of a set of possible states. Each state occurs at a particulate time. One of these states represents “now”, while the “past” consists of a linear discrete sequence of states occurring at the time before “now”.

**Definition 2. (State)** A state $s$ is a time point where some facts of SCQI hold true. These facts can be characterized by a set of logic propositions specifying what holds true at the time point. Each logic proposition is composed of (1) primitive propositions and (2) logic operators including propositional operators (“$¬$” (not), “$∧$” (and), “$∨$” (or)) and temporal operators (“$◊$” (sometimes), “$□$” (always), “$○$” (next)).

Note that the evolving of a state to a new one can be triggered by an event, which means the actions performed by agents cause the change in state. The modal connective “happens” is used to express the fact that some action happens.
Definition 3. (Event): An event e is an observable occurrence, the happening of which will trigger the evolution of a state to a new state. The happening of an event e is denoted by $\text{happens}(e)$.

Using a modeling structure of decision trees, there will be a number of possible future states triggered by the happening of events. Each node in the structure represents a certain state, and each branch in the tree represents an alternative execution path. For every path connecting a current state $s_i$ and a future state $s_j$, there exists an event $e$, the happening of $e$ leads the $s_i$ evolve to $s_j$.

Definition 4. (Path): A path is a connection between two different states. The path from state $s_i$ to state $s_j$ represents the transition from $s_i$ to $s_j$, denoted as Path ($s_i, s_j$). $\forall$ Path ($s_i, s_j$) $\Rightarrow \exists e$, $\text{happens}(e)$ leads the $s_i$ evolve to $s_j$.

To express the properties that quantify paths, we use “$A$” and “$E$” to express all paths and some path, respectively. In other words, $A\phi$ means $\phi$ is true on all paths in the future, while $E\phi$ means $\phi$ is true on some optional path in the future.

A supplier’s possible world consists of a sequence of states indicating the past, a state indicating the present, and several alternative paths to future states. Each state occurs at a certain time point and can be characterized by a set of logic propositions specifying what holds true at that time point.

Definition 5. (Supplier’s possible world) A supplier’s possible world is defined as a tuple $w = \langle S, L, E, H \rangle$, where $S$ is the set of states; $L$ is the set of value assignments to $\{\text{sc, p, ip, q1, sr, rev}\}$ at each state $s \in S$ in $w$, $E = \{qp, qd, np\}$; and $H$ is a set of relations on the $S$ and $E$, i.e., $H \subseteq S \times E \times S$.

Figure 2 shows an example of the possible world of a supplier named Corp. Sanl. This possible world, denoted by $B_{ini}$, is marked by the time point of the current state $S_{ini}$, i.e., 3 August 2006. There are three options for the supplier to choose from, leading to three possible future states. With the assignment of different primitive propositions in future states, the supplier knows he may generate a revenue of $5, $-12.5, or no revenue after he performs one of the options.

The BDI logic incorporates modal connectives BEL, DES, and INTEND to represent belief, desire, and intention respectively. Take BEL, for example: $\text{BEL}(\text{Buyer}(x))$ is a term asserting that the supplier believes $x$ is a buyer; $\text{BEL}(\forall x \cdot \text{Buyer}(x) \Rightarrow \exists y \cdot \text{Supplier}(y) \land \text{SupplyContract}(x, y))$ is a phrase asserting that the supplier believes for every supplier $x$, there is a supplier $y$ such that $y$ supply products to $x$.

To model what a supplier believes, desires, and intends, we use belief-, desire-, and intention-accessibility relations, respectively, to link different possible worlds. When the world evolves, we say the world is in a new state in which new facts hold and the sets of belief-, desire-, and intention-accessible worlds have been altered. In other words, beliefs, desires, and intentions have changed. A proposition $\phi$ is said to be believed to be in a current state, denoted by $\text{BEL}(\phi)$, if and only if it is true in all its belief-accessible worlds in the current state. So it is with desires and intentions, denoted by $\text{DES}(\phi)$ and $\text{INTEND}(\phi)$.

Definition 6. (BDI Model for Quality Inspection) A BDI model for quality inspection is defined as a 5-tuple, $M = \langle W, B, D, I, Sc \rangle$, where $W$ is a set of a supplier’s possible worlds $w$, and $B$, $D$, and $I$ map the
actual world to the belief-, desire-, and intention-accessible worlds, respectively, i.e., $B \subseteq W \times Sc \times W$, $D \subseteq W \times Sc \times W$, and $I \subseteq W \times Sc \times W$, where $Sc$ is the set of the current states shared by the actual world and the belief-, desire-, and intention-accessible worlds.

![Diagram](image)

**Figure 3. Example of a BDI model**

For example, Figure 3 shows part of a BDI model of a raw milk supplier. On 3 August 2006, $S_{ini}$ is the current state shared by the actual world $A_w$ and the belief-accessible world ($B_{ini}$), the desire-accessible worlds ($D_{ini1}$, $D_{ini2}$), and the intention-accessible world ($I_{ini}$). In the belief-accessible worlds, the facts such as inspection policy, optional get revenue, and optional get punished hold true. Thus, these facts are believed by the supplier in $S_{ini}$. The supplier has two desire-accessible worlds, $D_{ini1}$ and $D_{ini2}$. The proposition of being punished holds true in one desire-accessible world, while it is false in the other. Thus, the supplier does not desire to be punished since the proposition of getting punished does not hold true in both his desire-accessible worlds. Moreover, there is one intention-accessible world, $I_{ini}$, in which the supplier intends to undertake quality production.

**Knowledge Reasoning Procedure**

To introduce the reasoning mechanism of the model, we first introduce the rules of formula satisfaction. Satisfaction of formulas, denoted by $\vDash$, is given with respect to a model $M$, a world $w$, and state $s_0$. The expression $M, w_{so} \vDash \phi$ is read as “the BDI model $M$ in world $w$ and state $s_0$ satisfies $\phi$”, while $M, Path^w(s_0,s_1) \vDash \phi$ is read as “the path from $s_0$ to $s_1$ in the world $w$ of the BDI model $M$ satisfies $\phi$”. The following are definitions of the semantics of state formulae and path formulae, respectively.

**Definition 7. Satisfaction rules of state formulas**

- The model $M$ in world $w$ and state $s_0$ satisfies $\phi$ if and only if $\phi$ is a primitive proposition holding true in state $s_0$.
  $M, w_{so} \vDash \phi$, iff $\phi \in L(w,s_0)$ where $\phi$ is a primitive proposition.

- The model $M$ in world $w$ and state $s_0$ satisfies $\phi \land \psi$ if and only if both $\phi$ and $\psi$ holds true in state $s_0$.
  $M, w_{so} \vDash \phi \land \psi$, iff $M, w_{so} \vDash \phi$ and $M, w_{so} \vDash \psi$.

- The model $M$ in world $w$ and state $s_0$ satisfies $\Box \phi$, if and only if there exists a $s_i$ belonging to $S_w$, the path from $s_0$ to $s_i$ satisfies $\phi$.
  $M, w_{so} \vDash \Box \phi$ iff $\exists s_i \in S_w$ satisfying $M, Path^w(s_0,s_i) \vDash \phi$.

- The model $M$ in world $w$ and state $s_0$ satisfies $\exists \phi$, if and only if for all $s_i$ belonging to $S_w$, the path
From $s_0$ to $s_1$ satisfies $\varphi$.

$M,w_{s_0} \models \forall s_1 \in S_{s_0}$, satisfying $M$, $\text{Path}^w(s_{0},s_{1}) \models \varphi$  

#the model $M$ in world $w$ and state $s_0$ satisfies $\text{BEL}(\varphi)$, if and only if for all state $v$ in belief-accessible worlds, the $\varphi$ holds true in state $v$.

$M,w_{s_0} \models \text{BEL}(\varphi)$ iff $\forall v$ satisfying $(w,s_0,v) \in B$, $M,v_s \models \varphi$  

#the model $M$ in world $w$ and state $s_0$ satisfies $\text{DES}(\varphi)$, if and only if for all state $v$ in desire-accessible worlds, the $\varphi$ holds true in state $v$.

$M,w_{s_0} \models \text{DES}(\varphi)$ iff $\forall v$ satisfying $(w,s_0,v) \in D$, $M,v_s \models \varphi$  

#the model $M$ in world $w$ and state $s_0$ satisfies $\text{INTEND}(\varphi)$, if and only if for all state $v$ in intention-accessible worlds, the $\varphi$ holds true in state $v$.

$M,w_{s_0} \models \text{INTEND}(\varphi)$ iff $\forall v$ satisfying $(w,s,v) \in I$, $M,v_s \models \varphi$

**Definition 8. Satisfaction rules of path formulas**

#the path from $s_0$ to $s_1$ in the world $w$ of the model $M$ satisfies $\varphi$, if and only if in some optional future state $s_1$ after state $s_0$, $\varphi$ holds true in state $s_1$.

$M, \text{Path}^w(s_{0},s_{1}) \models \varphi$ iff $s_0 \times s_1 \in R_w$ and $M,w_{s_1} \models \varphi$.

#the path from $s_0$ to $s_1$ in the world $w$ of the model $M$ satisfies $\varphi \land \psi$, if and only if in some optional future state $s_1$ after state $s_0$, both $\varphi$ and $\psi$ holds true in state $s_1$.

$M, \text{Path}^w(s_{0},s_{1}) \models \varphi \land \psi$ iff $M, \text{Path}^w(s_{0},s_{1}) \models \varphi$ and $M, \text{Path}^w(s_{0},s_{1}) \models \psi$.

#the path from $s_0$ to $s_1$ in the world $w$ of the model $M$ satisfies $\text{happens}(e)$, if and only if there is an event $e$, the happening of $e$ leads state $s_0$ evolve to $s_1$.

$M, \text{Path}^w(s_{0},s_{1}) \models \text{happens}(e)$ iff $e \in E(w)$ and $(s_0,e,s_1) \in H(w)$

Based on these satisfaction rules, we can have some inference rules in the production or deception process. The first rule is the production rule (i.e., Rule.1). As mentioned, the supplier can estimate the product quality by the inputs of the production process. If he/she uses good raw materials and good manufacturing plants with a regular production process, the product will be expected to possess good quality.

**Rule 1. (Production Rule)**

$M, \text{Path}^w(s_j,s_k) \models \text{happens}(qp) \land qp = \text{QualityProduction}(p, PL, PC, RM, c, EQ, EA)$  

$\Rightarrow M,w s_k \models p = \text{Product}(EQ, EA)$

For example, if a supplier named Corp. Sanl carries out QualityProduction(Corp.Sanl’s raw milk, {healthy cow}, {good feed}, {regular procedure}, $6.5$, {protein 0.70, fat 0.75, antibiotic 0.1}), we can derive that Corp. Sanl’s raw milk would be product1({protein 0.70, fat 0.75, antibiotic 0.1}, {nitrogen 0.70, butter 0.75, antibiotic 0.1, m-attr 0.70, ...}). On the other hand, if Corp. Sanl carries out quality deception, the product attributes will be changed to the expected values. The quality attributes may still be at a low level but the measured attributes may increase to a high level because of the deception.

On the other hand, if Corp. Sanl carries out quality deception, the product attributes will be changed to the expected values. The quality attributes may still be at a low level but the measured attributes may increase to a high level because of the deception. This leads to the Rule 2.

**Rule 2. (Deception Rule)**

$M, \text{Path}^w(s_j,s_k) \models \text{happens}(qd) \land qd = \text{QualityDeception}(p, DM, PL, PC, RM, c, EQ, EA)$  

$\Rightarrow M,w s_k \models p = \text{Product}(EQ, EA)$
For example, if a supplier named Corp. Menin does QualityDeception(product1, {melamine, water, butter}, {unhealthy cow}, {bad feed}, {dilute procedure}, $3, {protein 0.40, fat 0.50, antibiotic 0.7}, {nitrogen 0.7, butter 0.75, antibiotic 0.2, m-attr 0.40,...}), we can derive that Corp. Menin’s product would be product2 ({protein 0.40, fat 0.50, antibiotic 0.7}, {nitrogen 0.7, butter 0.75, antibiotic 0.2, m-attr 0.40,...}).

The inspection process involves using an inspection method to measure the measured attributes of the product. The result of the measurement, i.e., the measurement point, equals the true value of the measured attribute multiplied by the precision level of the inspection method. When the precision level is higher, the result is closer to the true value of the measured attribute, and when it is low, it is further from the true value. Thus, we have an inspection rule as follow:

**Rule 3. (Inspection Rule)**

\[ M, w s_k \models qi = \text{QualityInspection}(ip, p, mp) \land p = \text{Product}(Qa, Ma) \]

\[ \land ip = \text{InspectionPolicy}(qr, ma, sp, c, pr) \land qr \in Qa \land ma \in Ma \]

\[ \Rightarrow M, w s_k \models mp = ma \ast pr \]

When the measurement point is in the range of the specification set of the inspection policy, it is assumed that the product has passed the quality inspection. Then, the buyer will pay the supplier the price defined in the supply contract. To represent this inference process, we have the following:

**Rule 4. (Payment Rule)**

\[ M, w s_k \models (\forall qr \in Qr (ip = \text{InspectionPolicy}(qr, ma, sp, c, pr)) \land \text{qi} = \text{QualityInspection}(ip, p, mp) \land mp \subseteq sp )) \land sc = \text{Contract}(su, bu, p, Qr, m) \]

\[ \Rightarrow M, w s_k \models rev = rev + m \]

The deliberating rule uses the knowledge in the belief- and desire-accessible worlds as input to derive the intention-accessible world, which shows all the actions required for the supplier to accomplish its goal. The basic idea is this: If a supplier has a goal \( \varphi \) and believes that event \( e \) leads to \( \varphi \), then the supplier intends to do \( e \). This rule can be formulated as follows:

**Rule 5 (Deliberation Rule)**

\[ \exists v, (w, s_0, v) \in D \text{ and } M, Pathv(s_0, s_i) \models rev \]

\[ \forall u, (w, s_0, u) \in D \text{ and } M, Pathv(s_0, s_i) \models rev_i \]

\[ rev \geq rev_i \]

\[ \exists v', (w, s_0, v') \in B, s \in Sv', \text{ and } M, Pathv'(s_0, s_i) \models \text{happens}(e) \]

\[ \Rightarrow M, ws_0 \models \text{INTEND} \text{ (happens}(e)) \]

For example, if Corp. Menin has a goal to maximize his revenue, and Corp. Menin believes that when it carries out QualityDeception(Corp. Menin’s raw milk, {melamine, water, butter}, {unhealthy cow}, {bad feed}, {dilute procedure}, $3, {protein 0.40, fat 0.50, antibiotic 0.7}, {nitrogen 0.7, butter 0.75, antibiotic 0.2, m-attr 0.40,...}), Corp. Menin would get the revenue maximized (compared with all the other situations and combinations), then Corp. Menin will carry out this action.

In order to continuing identify the actions a supplier may take, we develop an execution procedure to run the DSS model. It is a computing procedure for updating the domain knowledge within the knowledge representation framework, and reasoning the knowledge with the reasoning rules. Since the knowledge of a supplier changes over time, the belief- and desire-accessible worlds in the BDI model are different at various time points. Figure 4 shows how to adaptively update the knowledge in the belief- and desire-accessible worlds at different time points. At every time point, the supplier’s intention is analyzed.
At the beginning of the loop, the new facts of the inspection environment are collected to update the belief-accessible world. These facts can be manifested by relevant events, such as the identification of previously unknown deception approaches and changes to inspection policies. The new facts lead to the evolution of the actual world to a new state associated with new belief- and desire-accessible worlds. The knowledge in the desire-accessible world is also updated with the supplier's new goals. Next, the knowledge in the intention-accessible world is derived using the reasoning mechanism. If the procedure identifies that the supplier intends to take certain deceiving actions, an alert is signaled, and new suggestions will be given.

```
BDI-interpreter
Initialize-state();
Repeat
  belief-set := belief-updating(event-queue);    // reads the event queue and updates the belief sets.
  desire-set := desire-updating(goals);         // updating the desire sets with new goals.
  selected-intentions := deliberate(belief-set, desire-set); // generates a set of intentions.
  update-intentions(selected-intentions);       // push these selected intentions onto stack.
  screen-for-deceiving-intension();            // execution of intention stack to monitor deceiving actions.
  suggestion-optimal inspection policy;
End repeat
```

**Figure 4. Execution procedure**

**Evaluation of DSS for SCQI**

To validate our proposed approach, we develop a prototype of DSS within a simulated dairy production environment, and use a laboratory experiment with human subjects to evaluate the effectiveness of the prototype. The reason that we use laboratory experiment is to facilitate collecting 1) data of products' real quality, 2) inspection data, and 3) suppliers' hidden deceiving behaviors. In industry practice, there are some challenges to collect the data: 1) the data of products' real quality cannot be collected from neither buyers nor suppliers. Buyers have the inspection results, which may be inaccurate estimations of real quality because of inspection errors. Although the suppliers' inputs are the main determinants of real quality, there are some random effects in the production process. Thus the suppliers cannot precisely offer the data of products’ real quality. 2) suppliers are reluctant to reveal their deceiving behaviors in industry practice. These challenges can be solved by collecting data from the laboratory settings.

**Prototype Development and Implementation**

The purpose of the proposed approach is to serve as decision support tools for SCQI. More specifically, our decision support system is located on the buyer side, providing suggestions of quality inspection policies based on the analysis of the supplier’s intention, to avoid unnecessary inspection costs caused by excessive inspections and inspection errors caused by inadequate inspections. To demonstrate the system development process, we have built a prototype in a simulation platform for a dairy buyer to do quality inspection of raw milk from suppliers. Our prototype instantiation provides advice for raw milk buyer to carry out flexible inspection policies that minimizes inspection costs and inspection errors.

The prototype is embedded in a raw milk transaction system developed with JSP and MySQL. This transaction system is a simulation platform that includes both raw milk production from the supplier side and quality inspection from the buyer side. All of the participants produce, inspect, or trade products on this platform. The raw milk production process is simulated through the choosing of inputs such as feed, cows, and milking process by role players of suppliers. The raw milk is generated by a production function based on these inputs. The supplier can choose the quality inputs, as well as some quality deception methods.

When the supplier hands this product to the buyer, the buyer will carry out a quality inspection to decide whether to accept this product. Some of the real-time transaction information about raw milk suppliers is collected, such as the feed (i.e., raw materials), health status of the cows (i.e., plants), and the milking process (i.e., procedure). Our prototype serves as a decision support system for buyers to inspect the products. When the buyer click the button “DSS”, a text message will be delivered, stating the analysis results of the supplier's intention. This text message communicating the supplier’s intention is generated.
through a BDI component developed by Jadex (Pokahr et al. 2005), which is a BDI reasoning engine that allows for programming intelligent software agents in XML and Java.

**Experimental Evaluation**

To evaluate the prototype, we select a benchmark DSS to compared with, design hypotheses, and carry out an experiment with a rigor procedure and well-defined experimental settings. As far as we know from our literature review, there isn’t any available DSS designed for detecting the quality deceptions in SCQI by far. Therefore, we consulted three domain experts, who are from the dairy industry, about the decision supports they can offer as human industry experts for detecting the quality deceptions in SCQI. We compiled their suggestions as a benchmark, including several important criteria of quality inspection, and advantages and disadvantages of each inspection method. Figure 5 shows a comparison of the decision support messages from the benchmark DSS and BDI-DSS.

The evaluation in this research has a proposition: Using the BDI-DSS to model and infer the rational behaviors of suppliers will lead to enhanced decision performance of the buyer’s quality inspections. In line with the taxonomy proposed by Lilien et al. (2004), we assess the decision performance of subjects based on two criteria—the decision outcome and the experiment process—for which both objective and subjective evaluations are included. The decision outcome is manifested by the objective inspection results and subjective evaluation about the decision difficulty.

Inspection accuracy, inspection cost, and buyer profit are common objective indicators of the effectiveness of inspection policies (Baiman et al. 2000). Hence, we posit the following hypotheses about the objective evaluation of decision outcomes.

H1a: Using BDI-DSS will lead to higher inspection accuracy compared to the benchmark DSS.

H1b: Using BDI-DSS will lead to lower inspection costs compared to the benchmark DSS.

H1c: Using BDI–DSS will lead to higher buyer profit compared to the benchmark DSS.

Decision difficulty, a subjective indicator, reflects the degree of confusion, frustration, and difficulty the consumer perceives in making a decision (Iyengar et al. 2000). We have the following hypothesis regarding the subjective evaluation of decision outcomes.

H2: Using BDI-DSS will lead to lower decision difficulty compared to the benchmark DSS.
The experiment process, which involves the screening of information provided by information systems (i.e., supplier information, product information, information available through inspection technology, and decision support information on the supplier’s intention analysis), is characterized by the decision time and the perceived information satisfaction and system satisfaction during the experiment. Decision time, measured by observed experiment time spent to make decisions by the buyer, is an objective indicator of the amount of effort exerted to process information before a decision is made (Roberts et al. 1997). Thus, we have the following hypothesis about the objective evaluation of the experiment process.

H3: Using BDI-DSS will lead to less decision time compared to the benchmark DSS.

Information satisfaction and system satisfaction are subjective indicators reflecting the degree to which the subject perceives the information system to be capable of providing information and functions to meet decision-making requirements (Wixom et al. 2005). We have the following hypotheses about the subjective evaluation of the experiment process.

H4a: Using BDI-DSS will lead to higher information satisfaction compared to the benchmark DSS.
H4b: Using BDI-DSS will lead to higher system satisfaction compared to the benchmark DSS.

Experiment Setting and Procedure

The experiment was carried out in the context of quality inspection in dairy supply chains which consisted of a raw milk supplier and a buyer. At the beginning, the raw milk supplier chooses a quality level of cow, feed, and antibiotics respectively to produce the raw milk. The milking process can be: 1) at home, the supplier can dilute the milk to reduce cost, and add melamine or butter; 2) at the milking station, the supplier is under the supervision of the buyer and cannot do these deceptions. Finally, the supplier will submit the raw milk to the buyer. If his/her product passes the buyer’s inspection, he/she can get his/her payment; otherwise, he/she will not get payment.

When receiving the product, the buyer chooses different inspection methods to do the quality inspection. If there’s an inspection result under a certain level, the buyer can reject the raw milk. Because of imperfect inspections, there are two types of inspection errors that buyers may make. One type of error is accepting a product that is not qualified, while the other one is rejecting a product that is qualified. If the buyer makes either type of inspection error, he/she will lose the profit.

The ordinary product inspection standards are known to all entities in the supply chain. Product inspection is the responsibility of the buyer side; in other words, the buyer can inspect to a higher or lower standard than the inspection norm. Suppliers do not know how the buyer carries out the product inspection. We assume that the deception knowledge is common knowledge among the supplier and buyer; thus, deception knowledge is represented as predefined data in the database.

A total of 80 subjects, who are graduate students in a course on Supply Chain Quality Management participated in this study. They were randomly divided into 40 pairs. Each pair consisted of a supplier and a buyer. At the beginning of the experiment, the students first read the experiment instruction for 10 minutes, and then the teacher introduced the experiment procedure and the use of software for 30 minutes. Before the experiment, students were given a pretest related to their knowledge of SCQI and experiment. If students gave correct responses, then they are qualified to do the experiment.

Two rounds of experiment scenarios were used for practice. All sessions had to finish working through four scenarios of different information asymmetry situations, each consisting of around three rounds of transactions (subject to time limits). In order to eliminate the effect of contract sequence, we manipulated each session to begin with different contracts.

Table 3 describes the operationalization of the dependent variables. Note that buyer profit is a synthesized indicator of both inspection accuracy and inspection cost. The subject who gets a high inspection accuracy and low inspection cost can get a high buyer profit. The subjects are motivated to maximize their profit by prizes according to their performances.
Table 3. Operationalization of Dependent Variables

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Operational measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inspection accuracy</td>
<td>The percentage of accepting a high-quality product and rejecting a low-quality product in product inspection.</td>
</tr>
<tr>
<td>Inspection cost</td>
<td>The cost of the inspection process, including the cost of using different inspection technologies.</td>
</tr>
<tr>
<td>Buyer profit</td>
<td>The income of the buyer minus the inspection cost and the possible penalty due to inspection error.</td>
</tr>
</tbody>
</table>
| Perceived decision difficulty (Cronbach’s alpha = 0.778) (Source: (Iyengar et al. 2000)) | 1. The extent of confusion you may have when you make the decision.  
2. The extent of frustration you may have when you make the decision.  
3. The extent of difficulty you may have when you make the decision. |
| Decision time              | Time taken to make a decision, from when you received the product from the supplier to when you submitted your inspection policies.                   |
| Perceived information satisfaction (Cronbach’s alpha = 0.927) (Source: (Wixom and Todd, 2005)) | 1. Overall, the information I got from the system during the experiment was very satisfying.  
2. I am very satisfied with the information I received from the system during the experiment. |
| Perceived system satisfaction (Cronbach’s alpha = 0.861) (Source: (Wixom and Todd, 2005)) | 1. All things considered, I am very satisfied with the system during the experiment.  
2. Overall, my interaction with the system during the experiment was very satisfying. |

Results and Discussion

Individual characteristics such as age, gender, experience, and the skills of participants, which could affect decision-making approaches and outcomes, were controlled by means of randomization. Manipulation checks were also conducted to ensure that our manipulation of decision aids and contracts was successful. Further checks indicated no significant differences among participants in perceived confidence and knowledge by asking the participants to rate themselves on a 7-point Likert scale of their level of perceived quality management knowledge (supplier: F= 0.134, p > 0.1; buyer: F = 0.150, p > 0.1) and perceived confidence (supplier: F = 0.091, p > 0.1; buyer F = 0.203, p > 0.1) before the experiment. The time effect of learning curves was controlled by means of randomizing the sequence of contracts.

All statistical tests were conducted at the 5% level of significance. Table 4 shows the descriptive statistics of the dependent variables.

Table 4. Means (Standard Deviations) of Dependent Variables

<table>
<thead>
<tr>
<th>Decision Support</th>
<th>Outcome Measures</th>
<th>Process Measures</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inspection accuracy</td>
<td>Inspection cost</td>
</tr>
<tr>
<td>benchmark DSS</td>
<td>0.77 (0.421)</td>
<td>1.62 (1.800)</td>
</tr>
<tr>
<td>BDI-DSS</td>
<td>0.83 (0.381)</td>
<td>1.18 (1.197)</td>
</tr>
</tbody>
</table>

H1a posits that participants using BDI-DSS would get higher inspection accuracy than participants using Benchmark DSS. As predicted, our results show an improving effect of the BDI approach on the inspection accuracy. Comparing the means of inspection accuracy, we observe that BDI subjects have
significantly higher inspection accuracy than Benchmark DSS users (i.e., mean_traditional = 0.77, mean_BDI = 0.83; t = -1.478, p < 0.01). Hence, H1a is supported. H1b posits that participants using a BDI-based approach would get lower inspection costs than participants using Benchmark DSS. The results provide empirical support for this hypothesis by showing that BDI users spent significantly less on the inspection process (i.e., mean_traditional = 1.62, mean_BDI = 1.18; t = 3.148, p < 0.01). Similarly, H1c suggests that users of the BDI approach would get a higher profit than users of the traditional approach. The lower inspection costs and higher inspection accuracy lead to an increase in buyer’s income and a decrease in cost, and the empirical results support this very significant effect (i.e., mean_traditional = 0.55, mean_BDI = 1.42; t = -2.756, p < 0.01).

H2 posits that compared to users of Benchmark DSS, users of BDI-DSS would perceive less decision difficulty. Because BDI-DSS provides a useful analysis of supplier’s intention, users would process less confusion, frustration, and difficulty in making inspection policies. Results support this significant effect (i.e., mean_traditional = 4.5667, mean_BDI = 4.0833; t = 1.114, p < 0.05).

H3 suggests that users of BDI-DSS will spend less time on decision making. However, the empirical results do not support this hypothesis (i.e., mean_traditional = 82.8, mean_BDI = 69.65; t = 1.968, p > 0.1). That may be because the BDI approach did not show the details of specific inspection policies, but instead provides some suggestions, which leaves much room for subjects to consider their decisions.

H4a and H4b posit that, compared to participants using the traditional approach, those using the BDI approach would attain and perceive higher information satisfaction and system satisfaction. The results show that BDI participants perceived both higher information satisfaction (mean_traditional = 4.7500, mean_BDI = 5.4250; t = -1.653, p < 0.05) and satisfaction with their interaction with the system (mean_traditional = 4.9000, mean_BDI = 5.4250; t = -1.215, p < 0.05).

<table>
<thead>
<tr>
<th>Table 5. Independent T-test of Information Systems</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
</tr>
<tr>
<td>H1a: Inspection accuracy</td>
</tr>
<tr>
<td>H1b: Inspection cost</td>
</tr>
<tr>
<td>H1c: Buyer profit</td>
</tr>
<tr>
<td>H2: Perceived decision difficulty</td>
</tr>
<tr>
<td>H3: Decision time</td>
</tr>
<tr>
<td>H4a: Perceived information satisfaction</td>
</tr>
<tr>
<td>H4b: Perceived system satisfaction</td>
</tr>
</tbody>
</table>

Table 5 summarizes the statistical results from the laboratory experiment, which indicate that the BDI approach performs better than the traditional approach in terms of inspection accuracy, inspection cost, manufacturing profit, perceived decision difficulty, perceived information satisfaction, and perceived system satisfaction. These empirical results show the advantages of using BDI-DSS over the benchmark approach, and they illustrate the effectiveness of a BDI-based approach to the applications in SCQI.

**Conclusion**

In this study, we propose to address a vital problem for today’s supply chain quality inspections – quality deception – from a perspective of information collecting and knowledge reasoning. To design DSS based on information collected in supply chains, we present a knowledge representation framework, knowledge
reasoning rules, and an execution procedure. In order to illustrate the effectiveness of this approach, we build a prototype and use a laboratory experiment to demonstrate the prototype's superiority in supporting inspection policy making in supply chains.

We claim our contributions according to the criteria for assessing contributions of design science research (Gregor et al. 2013; Hevner et al. 2004; Venable et al. 2012). First, we present an approach of knowledge representation and knowledge reasoning to detect quality deceptions in supply chain quality deceptions. We show that this approach is implementable by developing a DSS prototype, and demonstrate its superiority. Second, we provides a new perspective to supply chain quality management that takes domain-specific knowledge and supplier's intention/behavior into consideration to make flexible quality decisions. It not only extends the existing SCQI literature, but also improves the knowledge base of agent-oriented and BDI modeling techniques by providing a real-world application. Third, the DSS development and evaluation process provide design science research contributions. We investigate the application of the proposed modeling approach in a real-world case of supply chain quality inspection. The evaluation of the proposed approach is in a laboratory setting, which facilitates the collection of suppliers' hidden behaviors of quality deceptions. This creative process offers an example for design science research to study the supply chain partners' hidden behaviors which could be unobservable from other investigation approaches.

The philosophy of this study is to model and analyze the rationale behind the quality deceptions in SCQI based on the assumption that suppliers are rational decision makers. As long as the supplier's behavior is in accordance with the belief-desire-intention theory (Bratman 1987), our approach should be able to detect quality deceptions based on the information collected from other supply chain contexts. Therefore, there are a number of possible research directions to further investigate the generalizability of this approach. First, we will apply this approach in other product domains, design and build quality inspection systems in other industries. Second, we will study more supply contracts to evaluate the effectiveness of proposed approach, especially the situations under which the suppliers may not be rational decision-makers.

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