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Andreas Thöni, Jack King, and Tjoa A Min, 2014, "ONGOING SOCIAL SUSTAINABILITY COMPLIANCE MONITORING IN SUPPLY CHAINS", Proceedings of the European Conference on Information Systems (ECIS) 2014, Tel Aviv, Israel, June 9-11, 2014, ISBN 978-0-9915567-0-0
http://aisel.aisnet.org/ecis2014/proceedings/track22/3

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Research in Progress

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Abstract

Social sustainability issues such as child labour at a supplier pose significant reputational risk for companies. Therefore, many companies now require that suppliers follow certain standards or codes of conduct. However, in today's complex supply chains with hundreds of sourcing locations, ongoing monitoring of compliance through audits for every supplier is hardly practical. Consequently, an information technology system is investigated as a tool to establish ongoing monitoring of suppliers based on available information with regard to the risk that suppliers breach the compliance rules defined. This paper describes work on a system that uses a Bayesian network to integrate evidence from multiple public and private data sources in order to rank suppliers dynamically. A particular focus of future work will be a prototype based on the issue of child labour and the advantages of applying text mining methods.

Keywords: Supply Chain Risk Management, Social Sustainability, Supplier Ranking, Ongoing Supplier Monitoring.

1 Introduction

This paper describes current work on a system using Bayesian networks (BN) to combine evidence from public and private information sources in order to continuously monitor compliance risk with regard to social sustainability of suppliers while specifically focusing on the data and model integration task.[1] Consequently, it aims at introducing a new information system that allows supply chain or sustainability executives to more efficiently monitor their supply chain with regard to social sustainability risk by allowing them to better justify the need for audits and by reducing the amount of manual work needed. Over the last several years, sustainability has not only become a major topic in the public opinion, but also in the domain of supply chain management (SCM). Organizational reputation can suffer severe damage due to unsustainable sourcing activities (e.g. World Economic Forum, 2012). Social sustainability, focusing on factors such as human rights or forced labour, can have a significant effect on a company's image, as companies are increasingly seen as responsible for their suppliers' potential misbehaviour (Klassen & Vereecke, 2012).

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[1] This work builds on ideas published in (Thöni, 2013).

Therefore, many companies have introduced codes of conduct and sustainability standards that guide supplier behavior (Ciliberti et al., 2008). Using these standards, a varying number of suppliers are subsequently reviewed and audited in regular intervals (Klassen & Vereecke, 2012). However, due to the large number of suppliers in today's complex supply chains and associated costs (Kogg & Mont, 2012), effective ongoing verification of the compliance to these standards is not widely implemented. Given that supplier internal information is typically only available through audits, certifications, or supplier communication (e.g. Klassen & Vereecke, 2012), there is an associated lag in the time between subsequent compliance verifications when they are performed. Public information may be able to be used to overcome the time lag between supplier reviews as well as enhance available data. Ongoing input from news sources or social networking may also help to identify relevant events. These events could be based on geographic, sector, and production-specific relations (see e.g. UNEP, 2009) or on other cause and effect relationships derived from literature related to a specific social sustainability issue such as child labour.

As a result, and given the amount of data available, information technology (IT) can be seen as a tool to support monitoring the compliance risk of suppliers using supplier internal and external inputs. Large BN have become technically feasible (Pai et al., 2003; Wooldridge, 2003), have been implemented for risk management (Lockamy III & McCormack, 2012), and are noted for their clear and explicit treatment of uncertainty in information (Reckhow, 1999). Moreover, BN can be configured using disparate inputs, including quantitative, statistical, and subjective expert information (Wooldrige 2003).

The remainder of this paper is structured as followed. First, section 2 reviews existing literature on ranking of suppliers with regard to sustainability. Section 3 presents our approach in more detail, and finally, section 4 summarizes the work in progress and future research direction.

2 Related Work

The core of the proposed system is concerned with developing an ongoing ranking of suppliers based on their risk of non-compliance with social sustainability standards. This ranking is developed using public combined with internal information in a BN. To the best of our knowledge, there is no existing work that addresses ongoing compliance risk for social responsibility in this manner.

BN are based on the Bayes' Theorem and are a combination of a Directed Acyclic Graph together with a joint probability distribution on the vertices of that graph. A BN has to fulfil the Markov condition requiring conditional independence for each node from its non-descendents given its parents (Neapolitan, 2003). BNs have been widely applied in monitoring and detection systems for some time, including applications such as treaty verification (King, 1996) or intrusion detection (Sebyala et al., 2002). Several papers have introduced BN to the field of supply chain risk management. Pai et al. (2003) focus on security by analyzing different risk management approaches for use in supply chain risk management. Lockamy and McCormack (2012) as well as Lockamy (2011) extend this and describe how BN can be used to model supplier risk. While they include environmental factors in their approach, they do not consider the integration of public information. Nevertheless, they do include a notion of compliance testing when implementing disruption risk. With similar restrictions, other SCM researchers have also used BN in the past (Meixell et al., 2008; Shevtshenko & Wang, 2009; Makris et al., 2011). Li and Chandra (2007) suggest an abstract dynamic BN model to deal with complex networks. It can be used to integrate information from different dispersed sensors in order to evaluate the status of a complete supply chain. They specifically propose the BN for adaptive data integration in a complex supply chain setting and also focus on sensor configuration while not addressing the sustainability context. Additionally, their aim is broader and more generic as they try to capture the state of the overall system. Häni et al. (2003) present a very specific assessment tool for firms based on the philosophy of "states" and "driving forces" without IT-based updating.

In supplier selection, papers have strongly emphasized calculation frameworks when dealing with ranking. In general, the selection of suppliers has been seen as a multiple-criteria decision making task identifying the optimal supplier(s) or ordering all suppliers (see e.g. Bhutta & Huq, 2002). For this general task, different approaches have been presented (de Boer et al., 2001; Tang, 2006), including models using weighting, total cost of ownership (TCO), mathematical programming, statistics, simulation, and Artificial Intelligence (AI). TCO approaches need cost quantifications which are difficult if reputational damage is concerned (Lemke & Petersen, 2013). Simulation models mostly vary a set of parameters for scenario testing and are not concerned with ongoing data integration. While statistical models dealing with uncertainty as well as AI methods seem of interest, none have been presented in the contexts of ranking and (social) sustainability for supplier selection. Suggested weighting and mathematical programming models are predominantly focused on how good a supplier fulfils a set of criteria (de Boer et al., 2001) and not with how much evidence is available conflicting with a given hypothesis and uncertainty.

Given the nature of supplier selection, neither papers focusing on defining weights (Xu et al., 2013; Chiou et al., 2011; Godfrey & Manikas, 2012), nor papers on the combination with different calculation approaches deal with the problem of continuously integrating evidence from public sources into the ranking for the purpose of compliance and risk-level checking (see Azadnia et al., 2012; Bai & Sarkis, 2010; Zeydan et al., 2011; Diabat & Govindan, 2011; Wen, 2013; Büyüközkan & Çifçi, 2011).

Supplier performance management is concerned with an ongoing evaluation of suppliers. Authors increasingly suggest that performance management should also cover sustainability measures (Cuthbertson et al., 2011). However, recent supply chain performance and metric literature includes sustainability measures only to a limited extent (Gopal & Thakkar, 2012; Cuthbertson & Piotrowicz, 2008; Gunasekaran & Kobu, 2007). If covered, the focus often is on the environmental dimension of sustainability and to a lesser extent on the social dimension (e.g. Hervani et al., 2005; Olugu et al., 2011; Shaw et al., 2010; Cuthbertson & Piotrowicz, 2008). Moreover, approaches are often specifically focused on metrics (e.g. Clift, 2004; Hutchins & Sutherland, 2008). A particularly relevant suggestion to measure sustainability comes from (Erol et al. 2011) who develop an overall indicator representing sustainability performance. The authors also include an alert system based on thresholds, but do not discuss the continuous integration of public information. While other authors have also addressed the topic of measuring social sustainability (e.g. Nikolaou et al., 2013; Hubbard, 2009; Hsu et al., 2011; Dreyer et al., 2005; Searcy et al., 2007), they have not addressed the question of continuous data integration for monitoring. Suggested systems relevant in a social sustainability context do not include a discussion of automated public information integration nor explicitly treat compliance analysis. This is to some extent also true for more general sustainability frameworks that provide companies with guidance on sustainability such as the Social Accountability Standard SA8000 (Social Accountability International, 2008).

3 Approach

This paper suggests an IT system that implements a Bayesian network for each supplier in order to calculate a ranking with regard to the likelihood of breaching social sustainability compliance standards. We propose starting with the initial hypothesis that a supplier conforms to given, pre-defined social sustainability standards and then calculate a relative measure for the likelihood of the hypothesis being false. An IT system is developed that can be used to gather and combine evidence on the likelihood of a compliance breach. Hence, computing the likelihoods for individual suppliers and relating them can provide a relative risk ranking. Figure 1 presents an overview of the system.

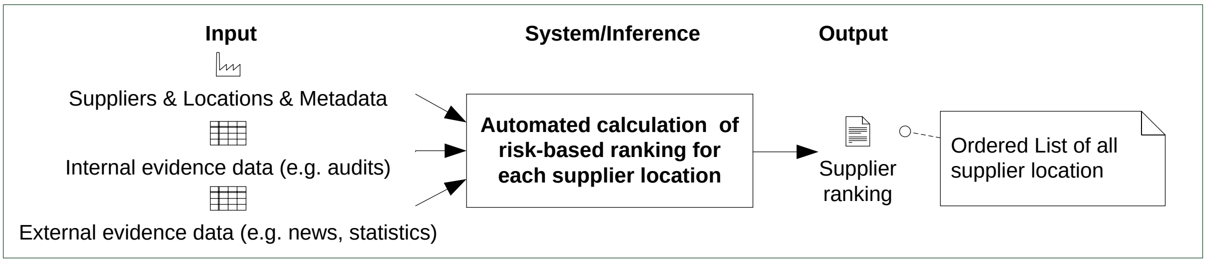

Figure 1. Generic system overview

The IT system should be able to use data from multiple sources and combine it using a Bayesian network. Comparing the compliance risk for different supplier locations can help to establish an ordered list of suppliers to be used for further investigation, review and auditing.

3.1 Data

Besides additional metadata (e.g. company, location, sector, etc.), the information integrated into the model for a firm should come from both internal and external sources. Company internal data can include historical audit results or experiences from personal or shared supplier history records. In a first version this requires data from previous audits of a supplier, particularly the time since the last audit and its result.

In contrast, further rating-relevant data could come from public statistical sources such as World Bank, Eurostat, or Transparency International data sets. This information is required to derive a prior likelihood for a particular supplier location which can depend for instance on the geography and the sector of a supplier. For example, in a child labour context, data could include child labour rates from World Bank (The World Bank Group, 2013) or critical goods lists per country from the US Department of Labor (U.S. Department of Labor, 2013).

Moreover, since a key feature of the system is an ongoing validation of compliance for suppliers, a continuous stream of input data is required. Due to the fact that input from suppliers, certification processes, and audits (mainly internal) can only be updated in defined or irregular intervals, important external evidence data may be potentially derived from frequently updated sources such as news or other dynamic public information like Twitter feeds and referenced content. Here, a text mining system can extract relevant data from news or other items in order to be able to relate a certain news text to a specific supplier. Additionally, a classification algorithm can help to decide whether a particular news article contains an incident or just a normal story. For example, given an incident and depending on how geographically close a certain incident is to a related supplier location, the assessment may more or less strongly be influenced. This will be a key feature of the planned research. Nevertheless, the information that will be included is limited to online retrievable sources. Additional channels (e.g. manual input by local NGO representatives) could be a suggestion for future research.

In any case, a clear cause and effect relationship between a data item used and the social sustainability risk level at a supplier location needs to be shown before integrating a statistic, news evidence source or other data item into the model. This, as well as necessary data transformations through e.g. text mining are also part of the ongoing work.

3.2 System/Inference

To process the data, a Bayesian network is suggested to combine evidence for each supplier. The Bayesian network will produce a likelihood level for a social sustainability compliance issue at a specific supplier location that can be then used for ranking. The initial BN will assume that a supplier does not breach a code of conduct or contract. Each piece of evidence collected will lead to an updated graph and a recalculated likelihood for the supplier.

BN rely on classical probability theory, allow one to explicitly account for uncertainty (Uusitalo, 2007), and their structure and results can be easily understood by non-domain experts (Reckhow, 1999). In general, BN have become especially popular over the last decade as recent implementations can now handle a significant amount of variables for practical purposes (Pai et al., 2003; Wooldridge, 2003). As depicted, BN are modelled with a directed acyclic graph where nodes represent variables and arcs between nodes represent conditional dependencies between them (Charniak, 1991; Uusitalo, 2007). Figure 2 depicts an exemplary BN having five variables.

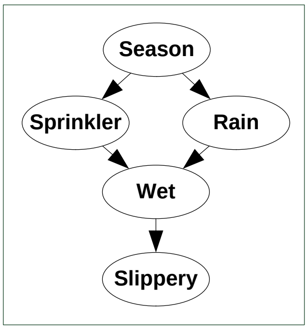

Figure 2. Exemplary Bayesian Network (Pearl, 1997)

In this simple example of a Bayesian network we model our understanding of the connection between the season of the year, the status of a sprinkler, the presence of rain, the wetness of the pavement and whether the floor consequently is slippery. The network includes our belief that the effect of the season on the slippery variable can be expressed through intermediary variables. Thus, the BN represents a model of a certain environment in which e.g. the wetness depends on the status of the sprinkler and the evidence of rain. Mathematically this is expressed by a conditional probability that only depends on the predecessors of a certain node. In the specific example this would be P (Wet | Sprinkler, Rain). The joint probability distribution then is the multiplication of all nodes' conditional probabilities (Pearl, 1997). In the specific context of this paper, initial conditional probability tables for the BN (priors) will be partly derived from statistical data and partly with the help of domain experts (see e.g. Wooldridge, 2003). In a first top-level suggestion the Bayesian network will build on three input nodes that together are used to determine the breach likelihood for a specific supplier location. Figure 3 presents this initial model.

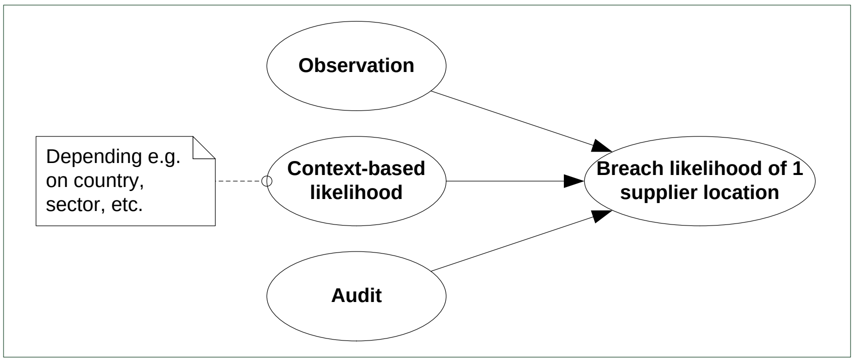

Figure 3. Generic initial suggestion of a Bayesian Network

A central element of the BN will be the prior information derived from external sources given the context of the supplier location. This will be complemented with results from internal audits and external observations from e.g. text sources. All parts can be extended if needed with additional attributes. Through a process of updates new news observation or also audit evidence can be included continuously and the likelihoods will be updated respectively (i.e. learned from frequencies; Neapolitan, 2003).

Given the independence assumptions between nodes, updates of a BN can be done swiftly as only incremental input for the affected parent and child nodes are needed.

3.3 Output

As described, the final result of the approach will be an ordered list of all suppliers with regard to their risk of conflicting with social sustainability requirements. This list can be used in order to improve the efficiency and the effectiveness of deploying auditing resources. Additionally, it could function as an alerting service in day-to-day operations if data input is ongoing and timely.

3.4 Planned Prototype

Social sustainability risk management can include a large number of different factors including, for example, possible risks within labour practices or human rights (Nikolaou et al., 2013). Due to the fact that each of these risks may have different causes, this work will, as a first step, focus on child labour as one element of social sustainability where issues may result in severe reputational damage for a company and which is usually included in codes of conduct or other standards. Moreover, it is part of the International Labour Organization (ILO) conventions No. 182 and 138 (International Labour Organization, 1973; International Labour Organization, 1999). Furthermore, the work on ongoing data integration will be developed based on news texts. Finally, initial work will be restricted to certain domains or geographical areas given the availability of data. Other social sustainability elements apart from child labour could be included later by adapting the framework provided. However, they will not be part of the current work. The prototype is planned to be tested together with domain experts. Ratings and changes in the ratings should be discussed for specific supplier cases and scenarios of incoming evidence from new articles.

A scenario for the suggested prototype could be a company having suppliers in different regions around the world including a rural location in India. Based on available data, as described above, a prior likelihood for the likelihood of child labour could be calculated based on knowing e.g. the country, the sector and whether the location is rural or not. One option is to use World Bank data on child labour rates as one input in order to calculate these prior likelihoods, but also other data and indexes could be included. The BN can then be updated when a news or message is discovered that presents a child labour case in a close-by factory, thus, increasing the likelihood of a breach for the supplier location concerned. Similar updates can be incorporated when new audit results are received. If the likelihood of a breach for the supplier then surpasses the one of other supplier locations, the ranking of supplier locations is updated accordingly.

4 Summary and Outlook

This paper describes work on a novel IT system for monitoring suppliers with regard to social sustainability compliance. Compared to the existing body of knowledge, the work will try to contribute several elements: First, the system will specifically focus on compliance checking and ranking of social sustainability risks, thus introducing a new approach for sustainability risk monitoring. Second, the IT system will be designed to enable ongoing monitoring based on the inclusion of verified timely sources in order to reduce the social sustainability monitoring gap between subsequent supplier interactions. Finally, key public data will be identified that can be used as predictive indicators for social sustainability risks. In a first prototype, research will focus on child labour given its persisting existence and critical customer attention.

The ranking output of the system should allow managers to better control social sustainability auditing and direct resources where they are needed most. Moreover, ongoing monitoring would enable faster reaction to market events and better communication with customers. Overall, the research may be integrated into a broader enterprise-wide IT sustainability platform (Thöni et al., 2013).

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