Artificial Intelligence model for social sustainability risk management in the apparel supply chain

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Abstract

The social dimension of sustainability has received special attention from researchers and managers in recent years. However, in supply chain management, many unsolved problems prevent reaching a satisfactory level of sustainability. The purpose of this study is to use an Artificial Intelligence (AI) model, to identify risk probability in social dimension of sustainability when contracting suppliers in the apparel supply chain (SC). A Bayesian (belief) Network (BN) model is applied based on supply chain information of six global companies from developed countries and five focal companies from Brazil, a developing country. The originality of this work is the Bayesian Network model, which uses the Human Development Index (HDI) and Global Slavery Index (GSI) to determine the risk probability of non-compliance in social aspects in the SC, fostering the monitoring and control of social burdens in the SC. The interrelation between companies and different external source data can provide important information to help managers and practitioners for decision making to mitigate risk and improve transparency along the chain. The model has been applied to eleven companies of the apparel sector and the main results are the identification of the social risk probability levels. From these results, it is possible to identify where the main fragilities are, being an important tool for practitioners and decision-makers to better manage the social dimension of sustainability in the supply chain.

Keywords: Artificial Intelligence; Bayesian Network model, Sustainable Supply Chain; Social Sustainability, Apparel sector

1. Introduction

Sustainability has been a current concern in many industrial sectors, and in the apparel supply chain this is a critical aspect. This vulnerability is caused by rapid consumption and disposal, called *fast fashion*, as for the production process, which involves extensive use of natural resources and use of toxic products. Labour condition, low salary, unhealthy conditions, and exhaustive working hours are some of the main weaknesses (Giannakis and Papadopoulos, 2016; Song et al., 2017; Köksal, et al., 2017). The implementation of codes of conduct and audits as well as several actions of corporate social responsibility have been carried out to minimise these problems (Turker and Altunas, 2014).

However, global chains are often long and multi-level, making it challenging to ensure the full implementation and control of the actions defined on corporate codes of conduct. There are still many irregularities that demand from the focal companies' greater control in the different tiers of suppliers. One of the main tools to select and assess suppliers are the audits, but most audits are still in the first and second tiers of suppliers (Bubicz et al, 2020a; Bubicz et al, 2020b). In many cases, it is still possible to verify the transfer of control and responsibilities to subsequent levels of suppliers. Nevertheless, the high pressure from buyers to have low-cost products means low profit and, consequently, suppliers do not prioritise investment in sustainability actions. Even though companies are investing in joint actions with suppliers of different tiers, raising awareness and charging about the need for decent working conditions, there are still many irregularities in meeting minimum conditions such as a healthy environment and a decent salary. Audits are not enough, and external pressure from NGOs and government have been essential to increasing social responsibility to achieve a reasonable working standard along the supply chain (Dargusch and Ward, 2010). Extending the audits to all tiers is one of the battles of many social organisations that require brands to have control over the entire production process from raw materials to the end of the products life cycle and in this way be aware of the risk involved along the chain. In the last few years, there has been growth in audits on the second tier, and some initiatives on the third tier (Aßländer et al., 2016).

Focal companies report many actions, control tools, pressure, and benefits for suppliers to minimise the risk of non-compliance of codes of conduct. Most audits and controls besides the internal auditors involve different external stakeholders such as independent auditors, representative entities, industry associations and specialised consultancies (Köksal et al., 2018; Aßländer et al., 2016; Huq et al., 2014). These entities have made efforts to increase traceability and transparency along the supply chain, thus reducing the risks of negative social and environmental impacts. Having control over the supply chain and managing the risks of non-compliance is one of the biggest challenges for companies, as negative impacts can compromise their financial performance.

Sustainability is in the strategy of most global organisations, with commitments to act along the supply chain, monitoring the environmental and social performance of operations. However, there is still a long way to go to characterise these companies as sustainable (Bubicz et al., 2020b). In recent years there has been greater use of information technologies to improve performance in global chains, to reduce costs and increase the agility in the flow of information and products. The large volume of information generated daily is often not used effectively for decision making. Business Intelligence tools have been widely used to organise and manage this significant amount of data, and one of the biggest challenges is how to use the information available to improve the performance of supply chains and make them more sustainable (Hazen et al., 2016; Wu et al., 2017). Using the information generated internally by crossing it with valuable information from different stakeholders can provide an in-depth and assertive analysis, improving transparency and traceability at all supply chain levels and allowing uncertainties monitoring. In this way the decision making will be better supported to manage social sustainability risk on all tiers of the apparel supply chain (Wu et al., 2017; Baryannis et al., 2019).

In this context, the objective of this paper is to explore how a machine learning algorithm, such as Bayesian Network (BN), can be used to support the management of social sustainability in the apparel supply chain. By applying a Bayesian Network (BN), an Artificial Intelligence (AI) model, it is possible to identify the probability of risk level that companies are exposed in the social dimension of sustainability along the apparel supply chain. From the different source of data, like historical information from companies (e.g., total suppliers, suppliers by country origin, audits, non-compliance, social actions and projects), crossing it with different governmental and non-governmental data (e.g., Trade Information by buyers and suppliers countries, Global Slavery Index (GSI) and Human Development Index (HDI)), it is possible to build a probabilistic model for inference to help managers to make decisions, ensuring transparency and increasing compliance of the codes of conduct, mainly in the social dimension of sustainability. Based on previous studies in the apparel supply chain in developed and developing countries (Bubicz et al., 2020a; Bubicz et al., 2020b), it is possible to identify that the social sustainability is managed in different ways along the supply chain, especially in the process of suppliers selection, audits and transparency. The eleven leader companies in the apparel sector used in the previous studies, six from developed countries (Bubicz et al., 2020a) and five from Brazil (Bubicz et al., 2020b), were used in the current study.
Having the objective in mind, the Research Question to be addressed in this study is:

RQ. *How can managers leverage AI probabilistic inference models, such as Bayesian Networks, to identify the social sustainability risk probability and improve the management of social sustainability in the apparel supply chain?*

The rest of the paper is structured as follows: Section 2 outlines the theoretical background based on the literature addressing the artificial intelligence in supply chain and sustainability risk. Section 3 the data collection to develop the Bayesian Network are presented. Section 4 presents the BN structure and steps followed to build the model. Section 5 presents the results, discussion and contributions of the findings as well as the implications for theory and practice. Finally, in section 6, concluding remarks and future research are presented.

2. Theoretical background

Artificial Intelligence is not a new concept in the literature, but it is gaining more attention in different areas of research (Li et al., 2018). Characterised as machine intelligence, which is programmed to "imitate" human thinking to make decisions based on previous events (Cully et al., 2015; Domingos, 2015), AI has expanded its space in the management of companies. What is at issue, however, is not only the use of models to visualise data but the possibility of building algorithms for data management and the ability to answer managerial questions that management systems cannot address (Mnich, 2018; Min, 2010).

The so-called “Big data analytics era” opens up countless opportunities not only in the operational area but also in the strategic field (Li et al., 2018; Hazen et al., 2016). The use of historical data for decision making is common practice in companies, however in global supply chains, with a massive flow of information and with the increase of automatic systems, the management of a large amount of available data is a great challenge (Waller and Fawcett, 2013). The integration of different sources of information and also the ability to analyse different types of data simultaneously (audio, video, text and graphic images) makes it possible to expand data management and, consequently, risk management, expanding access to information to support decision making (Blake et al., 2011; Kumar, 2017).

In the apparel area, artificial intelligence models have been widely used, especially in retail, building omnichannel structures, monitoring consumer profiles and consumer behaviour (Guan et al., 2019; Liu et al., 2017; Ye et al., 2018; Lynch and Barnes, 2020). Uncertainty environments constitute a significant challenge for the sector, and this volatility creates financial risks (Routroy and Shankar, 2014). For example, in 2018 H&M, the second-largest company in the apparel sector, had negative financial results, generating brand value loss, because of excess inventory. According to the company's CEO, these losses occurred due to errors in the definition of production, and inadequate assessment of market trends (Russel, 2019).

AI models have become essential for greater agility and efficiency in decision making along the supply chain, allowing for better management of uncertainties and risks mitigation, especially in economic and environmental dimensions of sustainability (Baryannis et al., 2019; Hazen et al., 2016). From the literature review, it was not possible to identify studies that use Artificial Intelligence models exploring external data to analyse the risk probability only considering the social dimension of sustainability along the supply chain. To fill this gap, it is essential to identify AI models that enable to establish a cross-relationship between the different sources of data, but also a transparency policy of companies' data is a need to increase the accuracy of the analysis.

2.1. Artificial Intelligence and supply chain sustainability

Sustainable supply chains are characterised as those that have an integrated structure and work collaboratively between different tiers, with the common objective of meeting the three dimensions of sustainability, economic, environmental, and social (Seuring and Müller, 2008b; Liu et al, 2017). AI models have been used to increase integration, information sharing, evaluate and also to improve sustainability performance along supply chains (Khakurel et al., 2018). However, it still has a more specific focus on economic and environmental dimensions (Kuo et al., 2010). Equity between the environmental, financial, and social dimensions has not yet been achieved, and it is a challenge for organisations (Barbosa-Póvoa et al., 2018; Bubicz et al., 2019). Although there is a large availability of tools, a significant challenge for companies it is still the lack of consistent historical data regarding sustainability throughout the supply chain, which is a fundamental factor for a better sustainability performance assessment (Sarkis and Dhavale, 2015).

Literature shows that AI methods can be used in several different fields ranging from medical decision-making (Mazurowski et al., 2008), finance (Trippi and Turban, 1996), and others. Previous studies in business processes have shown that AI can automate processes, identify redundant tasks, and consequently reduce operational costs (Van der Aalst, 2016). Although with all these advantages, the application of AI methods in the scope of supply chains towards sustainability remains an open research question, and it is still in its early stages (Wu, et al., 2017).

Different AI applications, such as machine learning have been used to reduce losses and managing risk (Lamba and Singh, 2017; Raut et al., 2019;). Machine Learning is characterised as a subfield of AI (Domingos, 2015), and it is applied to solve operational performance problems along supply chains (Lima-Junior and Carpinetti, 2019). As an example, the sustainable procurement and supplier selection approached by Lamba and Singh (2017) using Big Data to improve the product quality control and, as a tool to predict failure in machines. Following, the supplier selection using a Bayesian framework, addressed by Sarkis and Dhavale (2015) that helps to identify the sustainability performance of the suppliers allowing to consider several data sources for decision-making. For global supply chains, the analysis of the operational sustainability practices in a developing country using Artificial Neural Networks was addressed by Raut et al. (2019). The result shows the positive impact of using machine learning models to improve and better manage sustainability performance, especially to improve cooperation and information sharing along the supply chain.

The choice of the type of AI model depends on the type of problem to be analysed and solved, the data available, and the type of relationships and data crossings that will be made to identify the risk probability, and thus, make decisions based in a set of different sources of evidence. In this case, BN is a suitable model to analyse environments with high levels of uncertainty, being a multi-entity that establish relations between the variables, building complex systems from a set of small parts (Griffiths et al., 2008; Koller and Friedman, 2009). ANN and Bayesian Network are two AI models widely used and present a high prediction accuracy for a broad set of data and may help to mitigate risks and improve sustainability (Koller and Friedman, 2009; Min, 2010). In artificial neural networks (ANN) labelled training data is needed so that machine learning can detect information patterns and generate outputs based on these labels (Raut et al., 2019), which limits the broader analysis. Bayesian Networks correspond to a compact representation of a joint probability distribution, and for that reason, they do not require labelled data to perform probabilistic inferences. Since the process of inference does not require any kind of learning process, then labelled data is not required, making this approach more suitable to address the proposed research question, rather than other machine learning approaches, such as ANN. This makes the analysis broader, with multiple data connections from different sources, augmenting the decision-makers intelligence towards a specific decision scenario.

2.2. Bayesian Network

The Bayesian (Belief) Network is a directed acyclic probabilistic graphical model that consists of a compact representation of a full joint probability distribution. Nodes represent a random variable and edges represent influences from a source node to a target node. Each node is followed by a conditional probability table that describes the probability distribution of that node over the parent nodes (Moreira, 2017). This representation enables the integration of qualitative analysis, from the *directed acyclic graph* (DAG) structure, and quantitative analysis, from the joint probability distribution (Korb and Nicholson, 2011). Probabilistic inference can be more efficiently computed by exploring the notion of conditional independence between variables (Dove, 2011; Russell and Norvig, 2010, pp. 510). Note that a random variable A, is conditional independent from a variable B, if and only if, knowing information about a third random variable C does not change the knowledge that we gain about variable A: Pr(A | B) = Pr(A | B, C). Based on Koller and Friedman (2009) Figure 1 shows the different relationships that BN can capture in three random variables. In Figure 1. (a), (b) and (c), knowing information about variable C will make variables A, and B conditionally independent. Which means that knowing about B will not make any additional changes in the knowledge about variable A. On the other hand, Figure 1. (iv), under full uncertainty, variables A and B are already conditionally independent on C, but knowing information about variable C, will make A and B lose the conditional independence and they will become dependent on each other. This understanding is essential for query mode, where each node has different answers because of the independence of the variables.

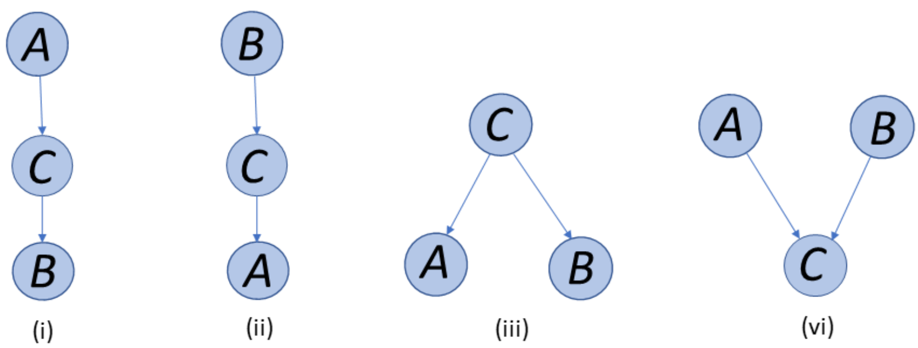


Figure 1 – Example of possible BN connections from *A* to *B* via *C,* (based on Koller and Friedman, 2009): (i) Indirect causal effect connection; (ii) indirect evidential effect; (iii) common cause; iv) common effect.

The great advantage of BN is the fact that it allows inferences under uncertainty, that is, it is not necessary to know a priori what variables are occurring to analyse the probability of the occurrence of a given event (Korb and Nicholson, 2011). It increases the intelligence of the decision scenario in a network structure that allows analysing, from a joint probability distribution which variables influence a given variable (to be analysed). Bayesian Networks also allow observing events that propagate information to other variables in the network and thus allow an analyst to check which variables are influencing the others. In the Bayesian Network, the graph model combining several modular parts that contain evidence for a deductive inference, in the same way of the human cognition (Pearl, 1988). In other words, it is an AI model to analyse and solve real problems based on probabilistic inference by combining different sources of information (multiple connections) in one single model.

Considering all the above BN properties and the objective of this study, a BN is applied to support decision making when managing supply chain sustainability, in particular by helping to identify the risk probability when contracting suppliers in the apparel supply chain.

The SamIam, a software toolkit for BN modelling and inference is used.

5.2.3. Sustainability risk

Risk analysis and risk management have been extensively addressed in the literature been one of the main concern among companies. In the last three decades, risk management has become more critical in the operational, environmental and social areas, with the increase in global operations, especially in long and fragmented supply chains (Freise and Seuring, 2015). With the global crisis of 2008, it took on even higher proportions, covering the entire supply chain with a focus on digitisation and greater information control (Thomas and Chermack, 2019). Analytical data management with a focus on risk prevention and mitigation has received attention in all business areas, increasingly using tools and information technology with a high capacity to assist in decision making (Baryannis et al., 2019; Trkman and McCormack, 2009). Risk, in the context of supply chains, is defined by Ho et al. (2015) as "the likelihood and impact of unexpected macro and/or micro-level events that adversely influence any part of a supply chain, leading to operational, tactical or strategic level failures or irregularities". It can be then defined as the probability of occurrence of a disruption in the cycle and the flow of the supply chain, varying the expected results and generating losses (Spekman and Davis, 2004). As disruption we have extreme cases like earthquakes, or facts like Rana Plaza collapse in Bangladesh in 2013 and the global health crisis by COVID-19 in 2020, unprecedented in recent history, that paralysed all operations, both global and local (Atsmon, et al., 2020). These cases have a substantial impact in the apparel industry that is translated into the social sustainability along the supply chain, as stated by Khurana and Ricchetti (2016) and Berg et al. (2020).

Companies have been working to minimise and mitigate sustainability risk that compromises their operations and image using as main indicators the ones following the GRI and SDG guidelines (Bubicz et al., 2020a; Bubicz et al., 2020b). The main categories of the risk management identified in the sustainability reports of the companies analysed are Economic, Operational, Environmental, Social, Legal, Corruption, Strategic and Image. The associated main characteristics are shown in Table 1. From the companies' reports, it is possible to identify that in general, the risk assessment has common characteristics. In the categories definition, sustainability dimensions are present, and corruption is a concern having special attention as risk category in almost 45% of the companies analysed (Inditex, H&M and GAP, global companies, Renner and Hering, Brazilian companies). In the global supply chain structure, the risk management and actions have special attention in the high-risk zones, being observed in Nike, Inditex, H&M and GAP sustainability reports. In the Brazilian context, special attention is in suppliers monitoring and control.

Regarding the responsibility in risk control, the sustainability and risk committees are the leading managers, usually integrated with audit teams. As stated by Aßländer et al. (2016) the audits have an essential role in identifying and managing risk, but to increase the audits is not enough if the causes of the problems are not detected and solved. The company Adidas is the only one that detailed the risk assessment system in its sustainability report, defining the risk categories and the improvement opportunities. The management process starts on Risk Identification, going to the Evaluation, Handling, and finally, on Monitoring and Reporting (Adidas Sustainability Report, 2018).

Table 1 – Main characteristics of the risk management assessment in the companies analysed.

Company	Risk Categories	Risk Management Assessment and Management	Responsible
Patagonia	Environmental Social	Measuring Impact Developing environmental and social standards Transparency Policy	Sustainability Committee
Nike	Economic Environmental Social	Suppliers Audits Stakeholders Engagement Risk Mitigation Guideline Focus Factories in High-risk Zones	Corporate Responsibility, Sustainability and Governance Committee
Inditex	Economic Environmental Social Corruption	Inditex's Compliance Model 5 Risk Policies - Prevention and Mitigation Risk Management and Control Systems Audits Risk Analysis, Prevention and Action Plan Risk assessment Suppliers Monitoring in High-risk Zones	Committee of Ethics General Counsel's Office
H&M	Economic Environmental Social Operational Corruption	Transparency Policy Stakeholders engagement Risk Mitigation Actions Task force on Climate Related Disclosure (TCFD) High-risk countries actions (suppliers) Sustainability risk assessments	Cross-functional forum Global Sustainability department National Monitoring Committees
GAP	Economic Environmental Social Operational Corruption	Risk-assessment system Suppliers monitoring Audits Country-specific strategies that take local context	Global Sustainability Team Internal audit team
Adidas	Economic-Financial Operational Legal and Compliance Strategic	Risk and opportunity management principles and system Risk management policy and Methodology/support	Executive Board Risk Management Department Supervisor Board Audit Committee

Renner	Economic Socio-Environmental Operational Corruption	14 Management policies for economic risk control 4 Management policies for socio-environmental risk control Supplier relationship management Leadership training to fight corruption	Audit and Risk Management Committee Sustainability Committee and the sustainability team
Malwee	Economic Environmental Social Operational	Internal Risk assessment - indicators Improvement actions - based on indicators and risk factor identified Audits Strategic partnership Program Focus on *Factions* and outsourcing control - High risk	Risk Committee - Multidisciplinary areas
Hering	Economic Socio-Environmental Operational Corruption Legal	Risk Matrix Suppliers monitoring Internal and external audits Stakeholders engagement	Sector managers Advisory Committees
Bibi	Economic Environmental Social Operational	Risk Management System - based on precaution and prevention Project "Bibi Non-Toxic Protection" (free translation) National suppliers' development as a priority	Sustainability Committee
Marisa	Economic Environmental Social Operational Legal Strategic Image	Risk Management Policy Internal Audits Risk Matrix - Probability X Impact Treatment, Control, Information and Monitoring	Internal Audits and Risk Committee Administrative council Financial Committee Managers Director

The application of these methodologies has been addressed by companies and researchers to better manage the supply chain risk proactively, especially with analysis and in-depth management of the big amount of data in a collaborative way (Zsidisin and Henke 2019). Song et al. (2017) have identified 20 sustainable risk factors in supply chain management by the literature and grouped into four types: operational, economic, environmental, and social. According to the authors, operational risk factors are interrelated to sustainability risks and may influence one another. Considering this statement, it is emphasised that the literature has shown the growing interest in environmental risk management and, in recent years, the relevant increase in the approach to the social dimension of sustainability, especially in the apparel supply chain (Bubicz et al., 2019; Rafi-Ul-Shan et al., 2018; Mehrjoo and Pasek, 2016; Freise and Seuring, 2015; Aßländer et al., 2016). Still, according to Spekman and Davis (2004), some types of risk in supply chains can be considered endemic. The ability to identify, manage and avoid risks related to the social dimension of sustainability is essential for companies to maintain their competitiveness (Carter and Rogers, 2008).

Environments with a high level of uncertainty contribute to increasing risk (Wu et al., 2017), especially with insufficient or missing data for correct decision making. The uncertainty associated with competitive environments fosters increased concerns and pressure to minimise risks so as not to make wrong or hasty decisions that could compromise financial results (Burke et al., 2019). Any negative impact has a direct impact on financial results, which may also compromise the solvency of companies. The higher the negative impact of an event, the higher its associated risk (Mehrjoo and Pasek, 2016). To better manage uncertainties and minimise risks, companies are increasingly looking for external data from different stakeholders that contribute to better design scenarios and increase assertiveness in decision making (Satpathy et al., 2015). In this context, the use of artificial intelligence tools has grown, and several techniques have been applied that increase the amplitude of data processing, beyond the limits of corporate operations to identify and reduce vulnerabilities (Baryannis et al., 2019). Thus, predictive analytics is at the centre of business and academic attention, being multidisciplinary and cross-sectional because it integrates knowledge and information from different fields to predict risk in supply chains (Baryannis et al., 2019; Hazen et al., 2016). One example is the use of external data to analyse disruption risks in SC, like weather reports and national and international policy.

Although studies are applying artificial intelligence to assess sustainability in supply chains, it is still restricted to a specific focus on management activities (Raut et al., 2019), operational areas (Kumar and Garg, 2017), or mainly the first tier supplier selection (Sarkis and Dhavale, 2015; Zimmer et al., 2017). Moreover, in these studies, the data used are internal, such as management and audit reports. There are no studies that apply to social sustainability covering all tiers of suppliers throughout the supply chain. There were also no studies using data from external stakeholders that could improve and broaden a predictive risk analysis for social sustainability along the supply chain.

To fill this gap is the main contribution of this work to provide a model that integrates external data from different stakeholders involved in the apparel supply chain to analyse better and manage the social sustainability dimension.

3 Data Collection

From the studies developed by Bubicz et al. (2020a) and Bubicz et al. (2020b), the present work is carried out using the real data identified for the apparel sector considering the supply chain network and social sustainability management previously analysed and compared.

The dataset was collected considering two types of sources: internal and external as described below.

3.1. *Internal dataset*

Internal data means a set of information regarding the supply chain entities, according to supply chain network structure of the global and Brazilian apparel supply chains (Bubicz et al., 2020a - Figure 5 and Bubicz et al., 2020b - Figure 2) and the social sustainability actions identified (Bubicz et al., 2020a - Figure 8 and Bubicz et al., 2020b - Figure 5). As the focus of this work is on the social sustainability dimension, only the upstream entities (see Figure 2) data is selected as it was previously identified that the main social problems are related to the upstream involved production process.

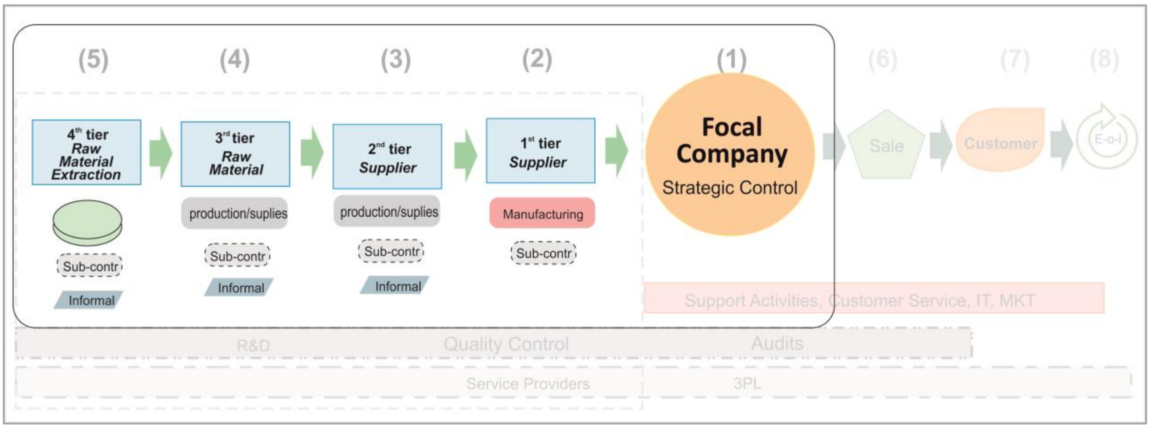


Figure 2 – Upstream supply chain entities based on the apparel supply chain network from Bubicz et al 2020a - Figure 5

In this study, only companies with control over the production process, supply chain stages and information of suppliers' multi-tiers were included. Consequently, Grendene, even though part of the case study in the Bubicz et al., 2020b, was excluded from this study because it presents few complete available data of suppliers that could influence the outputs, decreasing the consistency and accuracy of the model (Koller and Friedman, 2010). Data from sustainability reports, codes of conduct and information from websites to identify the key stakeholders were collected. The period of data is from 2014 to 2018.

Regarding suppliers' country of origin, companies present a list with the name of suppliers and address. From this information, it was possible to identify the suppliers' country of origin to each focal company. Some companies detail the tier of each supplier (especially global companies - see Appendix 5), the number of sub-contracts, the number of factories per supplier and the number of workers. However, there is no standard in the disclosure of information, and the data is not complete for all companies. Another critical issue is the fact that some companies often have few suppliers in a given country, but these suppliers have more than 5,000 employees in the same plant. In contrast, other companies have many SMEs suppliers, with less than 500 employees in each factory, or even less than ten. In order to maintain information integrity, a balanced dataset was considered involving a standard to all companies. Thus, information such as the number of suppliers and the number of employees per country were discarded. The option was then to include only the supplier's country of origin to hold a fairer analysis on risk probability. The suppliers' country of origin is identified per company in Appendix 1.

Data regarding the social aspects of social sustainability dimension were defined based on companies' sustainability reports and websites. Supplier audits, social actions and non-compliances per companies were considered (see Table 2). The analysis was carried out in the five years, from 2014 to 2018, and the result is summarized in Appendix 2.

Identified the leading suppliers of all eleven companies, the main internal data are described in Table 2.

Table 2 – Internal data collected regarding focal companies and suppliers

Heading	Description
Country Importing	Headquarter country of the focal companies analysed (based on the analysis developed by Bubicz et al., 2020a and Bubicz et al., 2020b).
Suppliers Country Origin	The suppliers country origin, based on the disclosed list by companies and web content mining (Appendix 1)
Supplier Audit	The type and quantity of suppliers' audits (total of suppliers' audits, critical supplier audits, technical visits - contractors and subcontractors) (Appendix 2)
Social Action	Actions and projects developed by companies: donations, community, suppliers (1st, and 2nd tiers), internal, raw material (based on the actions identified by companies in Bubicz et al., 2020a and Bubicz et al., 2020b) (Appendix 2)
Non-compliance	Total of non-compliances related to Labour Condition, Human Rights and Product Responsibility (Appendix 2)
Year	The period of data collected – 2014 to 2018

3.2. External dataset

External data means the set of information regarding external stakeholders, direct or indirect related to the companies that may influence the business environment, or gives information on relevant situations that are not considered by companies. Information that involves buyers and suppliers' countries (e.g., Human Development Index (HDI); Public Prosecution Service), as well as relevant information regarding Human Rights violations and degradant Labour Condition (e.g., Global Slavery Index (GSI); Newspapers), were considered.

To identify the data from companies that do not provide information on their suppliers, a web content mining technique was used linking the name of the companies with the words "supply", "supplier", "export", extracting information of unstructured data on the web. From the result, it was possible to identify the countries of some international suppliers, mainly of the Brazilian companies that are not disclosed in the companies' reports and websites. Also, this technique was an important tool to find information about non-compliance and conviction regarding HR and LC of the eleven companies analysed. The data mining technique was used to identify the variables on the collecting data and to define the information patterns according to the sustainability reports of the companies, following the Chapman et al. (2000) and Han et al., (2012) recommendations.

Labour condition and human rights data were identified on reports and websites of recognised Brazilian and international entities that monitor the apparel sector, being identified in the sustainability reports (Better Cotton Initiative; Textile Exchange; By Brazil Institute; Brazilian Textile and Apparel Industry Association (ABIT); Brazilian Footwear Industries Association (Abicalçados); Brazilian Footwear Industries Association (ABVTEX); Fashion Revolution), government (Brazilian Ministry of Economy; Brazilian Public Prosecution Office), and entities that work to promote human rights and labour dignity, fighting violations (The Global Slavery Index (GSI); PanMore Institute; Brazil Reporter - Escravo nem Pensar ("*Slave no way*" in the free translation of the author); Social Observatory; International Labour Organization (ILO); Business & Humanitarian Rights Resource Center; Thomson Reuters Foundation).

Such information, although, in some cases, not directly related to the companies, may influence the risk in contracting a supplier that does not meet decent working conditions.

Also, the leading Brazilian and international Newspapers were analysed to identify news about labour conditions and human rights related to the suppliers' working place of the Brazilian companies (on-line version): Folha de São Paulo, Estadão, Zero Hora, Correio Braziliense, BBC Brasil, O Globo, Estado de Minas, Valor, NY Times, Guardian, El Pais, BBC News and Al Jazeera. This information is essential to identify data of non-compliance that are not disclosed in the companies' reports to be compared with the data of the Brazilian Public Prosecution Office and the Brazilian Ministry of Economy.

The data of the eleven considered companies are presented in Appendix 2.

Additionally, Global Slavery Index (GSI) and Human Development Index (HDI) were included, being addressed in the literature as important parameters to identify the social non-compliance risk by authors like Parente et al. (2017), Sierra et al. (2018), and Cunha et al. (2019). GSI is developed by the Walk Free Foundation in collaboration with International Labour Organization (ILO) and International Organization for Migration (IOM) to estimate the number of people in modern slavery, monitoring data from 167 countries regarding Human Trafficking, Forced Labour and Slavery, and Slavery Like Practices (GSI Report, 2018). HDI (UN, 2020) is a summary measure of the average development performance of countries, considering longevity, education and standard of living. In the model, these two indexes were used interrelated with the supplier country of origin. As developing countries present a lesser control in fighting degradant working conditions (see Bubicz et al., 2020b) and present, in some cases, low GSI in compare to developed countries (see Appendix 3), HDI was added as an essential parameter to balance the results. It is important to point out that focal companies also have suppliers from their own country. When a country has a high GSI and low HDI, the risk increases, especially when focal companies (buyers) do not disclose suppliers' information. The relationship by countries buyers and suppliers' countries influences the social impact, and this has already been addressed in the literature by Pelletier et al. (2013).

The external data is described in Table 3.

Table 3 – External data collected regarding focal companies and suppliers' country origin

Heading	Description
GSI	Global Slavery index - per country (Appendix 3)
HDI	Human Development Index – per country (Appendix 3)
HR_LC_Conviction	Conviction by the focal company in Human Rights or Labour Condition, especially related to modern slavery and forced labour (Appendix 2).

As mentioned above to analyse the data, we performed a qualitative approach using the exploratory data analysis (Karlsson, 2009) applying the Bayesian Network Structure on the collected data.

4 - Bayesian Network Representation

The model is structured, using SamIam software and through the methodology depicted in Figure 5.3, following the steps by Huang and Darwiche’s (1996) as a guide.

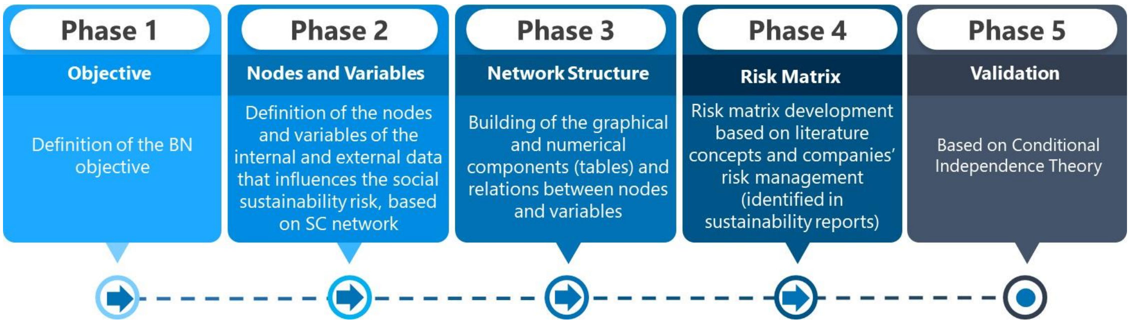


Figure 3 – steps to build the Bayesian Network model

4.1. Definition of the Network Objective

The main objective of the developed BN is to construct a model able to identify the risk probability on social sustainability that a company is subject when contracting suppliers, considering information from the own supply chain, also integrating external factors. Historical information from the supply chain entities, which is already part of the companies' risk monitoring is integrated with information from different external stakeholders, who can contribute to better manage vulnerabilities and act preventively. The construction of the model provides not only the possibility to identify the probability and the level of risk but also to identify the points of greatest vulnerability providing more assertive performance to mitigate them. Also, through the answer of a set of queries in the BN it is possible to identify the points that need control because only to increase audits is often not enough to solve the problems (Aßländer et al., 2016).

4.2. Nodes definition

The dataset to build the BN is defined considering the apparel supply chain structure and stakeholders activities identified in sustainability reports of the eleven companies analysed. Data is organised in “nodes” that represent the discrete random variables, according to Figure 4. Three main types of BN variables, which represent the network nodes, are described in the literature: (i) *Hypothesis variables*, that cannot be observed directly, (ii) *Information variables*, that represent observed events, and (iii) *Mediating variables,* for specific applications, which are not used in this study (Jensen and Nielsen, 2007). In the following sections, the nodes will be explained in detail.

4.2.1 Information Variables

Focal Companies

Focal company is the first node in the network. This is the basis of the network because it represents the companies that will take action when the risks of social burdens are identified. These companies are then the ones that will use the information provided by the model and will act to improve social sustainability. For this node, eleven companies were identified and modelled: (i) *Adidas*, (ii) *GAP,* (iii) *Inditex*, (iv) *H&M*, (v) *Nike,* (vi) *Patagonia,* (vii) *Bibi,* (viii) *Hering,* (xi) *Malwee*, (x) *Marisa,* and (xi) *Renner*.

Country Importing

One of the main aspects when assessing social sustainability in SC is the location of the headquarters of the focal company. This happens due to importation legislation and rules, which are different according to the geographic region (Pelletier et al., 2013). It is of paramount importance to include this aspect as a node in this network. Five counties, representing the headquarters of the eleven focal companies are therefore considered in the model: (i) *Brazil*, (ii) *Germany*, (iii) *USA*, (iv) *Spain*, and (v) *Sweden*. The identification of the headquarters location was based on the studies carried out in Bubicz et al. (2020a) and Bubicz et al. (2020b).

Suppliers Country of Origin

One of the main risk factors when dealing with social sustainability within SC is the supplier country origin, being this addressed in the literature in themes like low commitment in health and safety (Zsidisin and Henke, 2019), workers informality (Aßlander et al., 2016) and intensive labour (Zimmer et al., 2017). In the studied companies' sustainability reports it is also possible to identify concerns in social risk in countries identified as *High-risk Zones* (e.g., Nike and Inditex) and *High-risk areas* (e.g., H&M and Malwee). Seventy-seven suppliers' countries of origin were identified and considered in the model, which are related to the focal companies considered (see Appendix 2).

Supplier Audit

Audits are important means to assess suppliers' performance and to identify fragilities (Aßlander et al., 2016; Burke et al., 2019; Bubicz et al., 2020a; Bubicz et al., 2020b). They are constantly present in company reports and its results are widely used to guide social actions and corrective action plans to mitigate risks and improve supplier performance. In this model, the audits were identified based on companies sustainability reports, considering the period from 2014 to 2018, in four categories: (i)*Total audits*, (ii) *Critical Suppliers Audits*, (iii) *Technical Visits* and, (v) *Non-compliance* (total).

Social Action

As stated in Bubicz et al. (2020a) and Bubicz et al. (2020b), sustainability is in the strategy of the eleven companies analysed and based on this, social actions are developed in the different supply chain tiers as well as in communities to minimize social risk. These social actions identified in the SC entities in the previous studies were grouped in types of actions, observing the information of the companies' sustainability reports analysis. The following types of actions were considered: (i) *Community*, (ii) *First and second tiers Suppliers*, (iii) *Internal actions*, and (iv) *Raw material suppliers*.

Non-Compliance

From the sustainability reports of the companies and external stakeholder data (see section 3.2) it was possible to identify the audit process and the non-compliances related to the social dimension. The quantity and type of non-compliances identified were classified into three categories: (i) *Human Rights*, (ii) *Labour Condition*, and (iii) *Product Responsibility*. These are the leading social sustainability aspects treated as high social risk and high impact and are then the main focus of the social actions taken by companies in their supply chain activities as defined by (Bubicz et al. (2020a) - section 1 and Bubicz et al. (2020b) - section 1).

Year

This Year node allows to consider the evolution of the companies regarding their commitment to minimise negative social impacts. Considering the historical data it is possible to identify the movements and changes in social sustainability management, as well as the monitoring over the SC tiers (Köksal et al., 2018). This node is directly related to the nodes *Supplier Audit, Social Action* and *Non-Compliance*. The period of the analysis is from 2014 to 2018, being considered and modeled as (i) *2014*, (ii) *2015*, (iii) *2016*, (iv) *2017*, and (v) *2018*.

HR and LC Conviction

Conviction is the result of some failure in the supplier assessment and inadequate control of the audit process (Tilly et al. 2013; Huq et al., 2016; Mehrjoo et al., 2016; Burke et al., 2019). Consequently, the risk probability raises. Companies conviction regarding Human Rights or Labour Condition were identified. Only conclusive convictions were considered, with those that still have the possibility of appeals disregarded. This node is directly related to the focal companies in the model. It is a qualitative variable and the classification in the model is (i) *Yes* (company convicted) or (ii) *No* (company not convicted).

GSI – Global Slavery Index

Slavery-like condition is one of the most critical issues in human exploitation and is very present in the apparel sector. As previously mentioned, the GSI (Estimated prevalence of population in modern slavery - victims per 1,000 population) is identified in this model by suppliers' country of origin. The GSI scale is between 0 and 104 victims per 1000 population in the year 2018. In this model we only considered the countries related to this study, being between 0 and 17 (victims per 1000 population). This node is directly related to the supplier's country of origin, influenced by focal companies and their headquarter country. The node variables are classified as: (i) *0-1*, (ii) *1-2,* (iii) *2-3,* (iv) *3-4,* (v) *4-5,* (vi) *5-6, (vii) 6-7, (viii) 7-8, (ix) 8-9, (x) 11-12, (xi) 16-17.*

HDI – Human Development Index

HDI is considered taking into account that some countries are not transparent in government policies and inspection, being essential to balance and combine the indicators of this node with the node GSI. The HDI scale in 2019 was set to values from 0.470 to 0.946 (UNDP, 2019). This node is directly related to the suppliers' country of origin, influenced by focal companies and their headquarter country. In this model the variables are classified as: (i) *less 0.5*, (ii) *between 0.5_0.6*, (iii) *between 0.6_0.7,* (iv) *between 070.80,* (v) *between 08_0.9,* (vi) *greater_0.9.*

5.4.2.2 Hypothesis Variable

Risk

The node Risk is the main output of the model. By this node it is possible to estimate the risk probability in the social dimension, especially related to main social aspects: Labour Condition, Human Rights and Product responsibility. The risk categorisation was defined based on sustainability risk concepts (e.g., Ho et al., 2015; Song et al., 2017) and companies reports (e.g., Adidas Risk Management System, 2018, pp. 131; H&M Standard & Policies, Risk Impact Assessment and Monitoring, 2018, pp. 90; Inditex Risk Management and Control Systems, 2018, pp. 380; Renner Risk Management, 2018, pp. 16). The process of risk matrix modelling is detailed in section 4.4. This node receives all pieces of information and influences from previous nodes and the outputs for social risk probability are classified in six levels: (i) *Extreme*, (ii) *Very High*, (iii) *High*, (iv) *Moderate*, (v) *Low* and (vi) *Very Low,* based on the risk matrix levels.

5.4.3. Network Structure

After identifying the nodes that compose the model inputs, links and direct influences relation between nodes (arcs) have to be defined so as to estimate the probability and risk level. These relations are presented in directed arcs that represent the dependencies between variables (Koller and Friedman, 2009). As stated, the model is structured in SamIam software and the links were defined manually, by the help of four experts researchers. The first one is an expert in BN models, the second one is an expert in the apparel sector and risk management, and the other two are researchers with high skilled supply chain knowledge. The relationship between variables was exhaustively discussed and analysed in detail to identify connections that are related, defined considering the objective of the study and also in line with literature and companies sustainability reports.

The construction of this network structure considers the need to estimate the risk probability, using a query mode (Huang and Darwiche, 1996; Koller and Friedman, 2009). According to Koller and

Freednman (2009), the main critical components to building systems like BNs are *representation*, *inference* and *learning* being these elements crucial in answering queries. For example, *representation* is the graphical aspects of the *nodes*. Behind these nodes are the main characteristics and parameters of each *node* to be analysed and they must be consistent for *inferences*. The *learning* component is usually automatic, and the *learning* process occurs based on data provided and connections. That means it is possible to have a look at the outputs, observing each node and variables and their relations with the other variables. It also means that even with an estimated risk probability output, within the ranges of risk levels, it is also possible to identify each of the points related to this risk. Thus, it is possible to identify what are the main critical factors that contribute to increase the risk probability, and thus to act directly and assertively to reduce and mitigate. The final BN structure is presented in Figure 4.

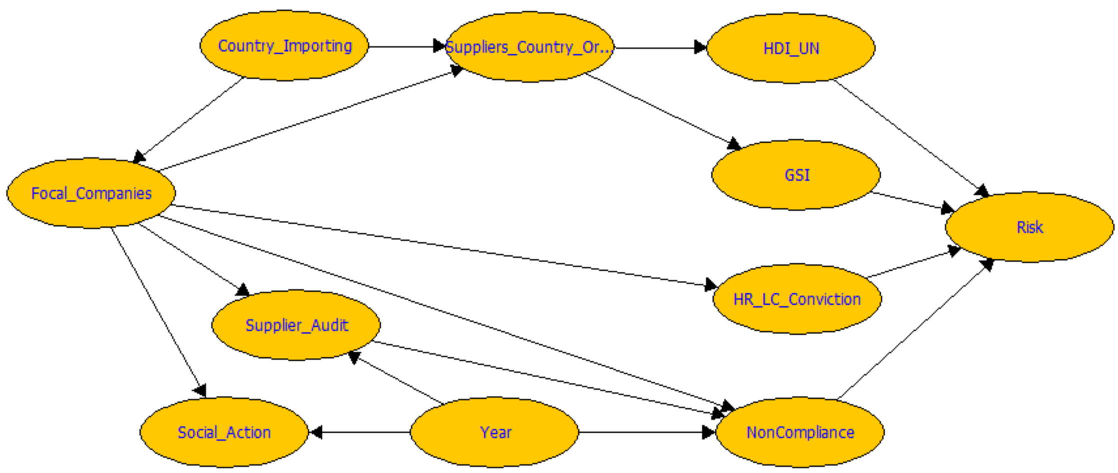


Figure 4 – Bayesian Network representation with the network structure and relationships between variables by SamIam software

4.4 - *Risk Matrix*

The risk matrix was developed based on literature concepts and sustainability reports of the companies analysed. Six levels were considered, as shown in Table 4, (i) *Extreme*, (ii) *Very High*, (iii) *High*, (iv) *Moderate*, (v) *Low* and (vi) *Very Low*. In the literature, the risk classification usually has three or five levels (Ho et al., 2015; Song et al., 2017). Our option was to expand to six levels, considering the objective of this model, not to assess risk, but a support tool to identify fragilities, based on companies actions and literature, and assist in decision making in risk mitigation. Greater amplitude in this model allows more detailed visualisation. In this way, it allows for more assertive decision making, especially when we consider the classifications of GSI and HDI, which have particular data in a vast universe with different and complex realities. Combining external data (“HDI” and “GSI”) by suppliers’ country of origin with internal supply chain data (Non-compliance and Conviction HR/LC (Ho et al., 2015; Arıoğlu et al., 2020) it is possible to identify some characteristics that influence risk probability. Conviction indicates some irregularity reported and identified along the supply chain, which can also indicate non-compliances not identified by the companies in the audits. The history of non-compliance, greater or lesser over the years, also influences risk, being interrelated in the model. As an example, Extreme risk probability means extreme impact, and mitigation plan should be in place, given the condition as low HDI and High GSI, adding non-compliances and/or HR and LC conviction. On the other hand, the high HDI and Low GSI mean *Very Low* risk probability, especially when presenting few non-compliances and no conviction. However, it is important to consider that *Very Low* risk probability does not mean inexistence of risk, and in some situations as slavery, the impact can be very high. Also, in these cases, mitigation and action plans are needed to manage the impact and reduce the consequences (Sýkora et al., 2018).

Table 4 – Risk matrix to estimate risk probability

Risk Level	**HDI**	**GSI**	**Conviction HR/LC**	**Non-compliance**
Extreme	Low (less 0.500);	High (between 11 - 17)	Yes or No	High (bet 0.8 – 1.0)
Very_High	Low (bet. 0.500 - 0.600)	High (bet. 8 - 10)	Yes or No	High (bet 0,7-0.8)
High	Medium (bet. 0.600 - 0.700)	Medium (bet 6 - 8);	Yes or No	Medium (bet 0,5-0.7)
Moderate	Medium (bet. 0.700 -0.800)	Medium (bet. 4 - 6)	Yes or No	Medium (bet 0,3-0.5)
Low	High (bet. 0.800 - 0.900)	Low (bet. 2 - 4);	Yes or No	Low (bet 0,1 - 0.3)
Very_Low	High (greater 0.900)	Low (between 0 - 2	Yes or No	Low (bet 0,0 - 0.1)

4.5. Validation

Once the BN structure had been defined, the validation is needed to identify if the model is according the scientific knowledge in risk probability, companies' actions and if the model is able to answer the research question. Different validation methods are identified in the literature for BNs and predictive models, especially using quantitative data for simulation models (Murray-Smith, 2019). As examples, Classical Hypothesis Testing to reduce errors and increase the confidence (Chen et al., 2004) and Probability Distribution to identify the discrepancies in data that can influence prediction (Ferson and Oberkampf, 2009). These types of known validation methods require similar types of data. As the present model is probabilistic and not predictive, involves different sources and different types of data, some of them that can be measured (e.g., audits number), and others that cannot be measured (e.g., the name of suppliers' country of origin) the validation process has to be developed in a specific way, considering the flexibility and the diversity of BNs and exploring expert knowledge (Mahadevan and Rebba, 2005; Keshtkar et al., 2013). The four experts' and researchers' knowledge were then used for a deep analysis of each node and their interrelation, based on literature concepts, and practices identified in the sustainability reports.

The main issue is to evaluate the performance of the automatic learning process, to be sure that the model can be able to "catch up" the distribution of all data provided and if the results are consistent (Koller and Friedman, 2009). All inputs and data were discussed and evaluated by four experts, in four steps (see Figure 5).

The first step was to identify the nodes and the relevance for the model and the influence of risk probability. In the second step, all the nodes were tested, identifying the companies and the output (risk level) related. The iterative process was carried out several times to identify errors, failures, and inconsistencies. The third step was to analyse the direct and indirect relationship between nodes and variables, and the influence in the outputs. In Bayesian Networks, the joint probability distribution considers and calculates all variables simultaneously to deliver the outputs that can be analysed from any node (Huang and Darwiche, 1996). Finally, in the fourth step, all nodes were tested and the information for each output was verified. The headquarter buyers' countries, node "country_importing", is directly related to the focal companies and it was purposely kept to maintain the independence of the information by country and not only by the companies analysed. It means that the model can also be used (in the future) by identifying the country of origin, including other buyer countries, without relating to any specific company.

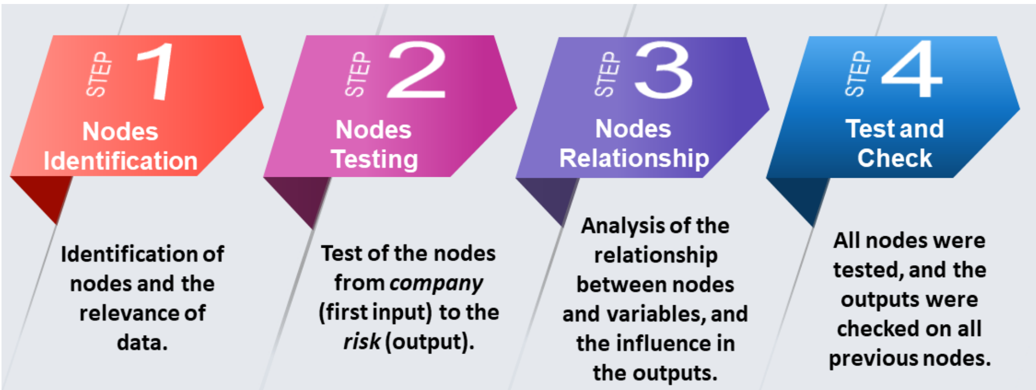


Figure 5 – The validation process of the Bayesian Network

5.5 - Results and discussion

The proposed BN model provides the risk probability analysis in six possible levels, given the presented data. The algorithm's output led to identifying the risk of non-compliance in the social sustainability dimension based on interrelation among the variables. These outputs can be observed from different perspectives, supporting decision-makers to identify the main fragilities, taking strategic actions to mitigate risk in supply chain proactively. It is important to note that this model is a sample of what is possible to infer given the data available. The results of the eleven companies selected and their supply chain data are now analysed and compared.

5.1. Social Risk Probability – Global perspective

The first result indicates the risk probability level of the eleven companies, as shown in Figure 6. It is possible to see the differences in the probability distribution of the risk levels for each company. The risk probability results of the eleven companies are in Appendix 4. From these results it is possible to infer that the company Bibi has a lower social risk probability, being 51.53% *very low* and 46.95% *low*. The lowest risk probability can be explained by the management strategy, being vertical integration, and local suppliers contracting as a priority. According to the company's sustainability report (Bibi Sustainability Report, 2018), this is the main way to increase control and minimise sustainability risks. On the other hand, two companies, Inditex and GAP, present the most expressive *Extreme* risk probability, 10.87% and 10.30% respectively. Inditex, GAP and Nike present similar distribution in risk probability, between 18.90% and 23.85% in *Very High*, between 30.26% and 37.88% in *High* level, between 25.52% and 29.74% in *Moderate* level. Company Marisa presents the highest risk probability index in *High level*, 53.33%. Adidas, Patagonia, and H&M present similar results in *Moderate, Low* and *Very Low* levels, being companies with low-risk probability. These companies present the lowest *High* (less than 12.03%)*, Very High* (less than 5%) and *Extreme* (less than 1.02%) risk probability index. These results are in line with the Fashion Transparency Index (published on April 22, 2020), being these three companies ranked in the top 10 in social and environmental issues. In the Brazilian Fashion Transparency Index (published on December 10, 2019) the companies Malwee, Renner and Hering are in the top 10 in transparency. Even these companies are in the top 10 no global brands scored more than 80% of 250 possible points. In the case of Brazilian companies, the situations is worst. No brands scored over 70%. It means that transparency was not achieved, and it has no control over the links in its supply chains regarding the social sustainability dimension.

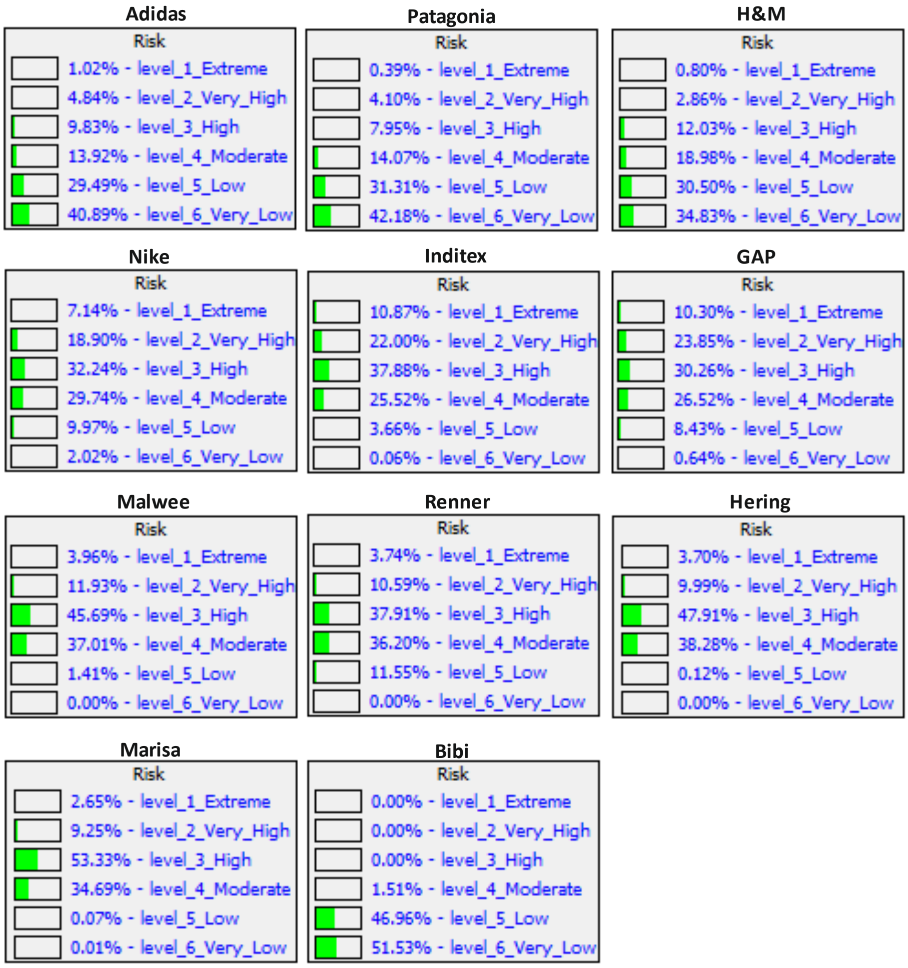


Figure 6 – Results of risk probability inferences per company based on the BN application

5.2. Exploring BN model

From this BN structure, information can be explored in two-folds. From companies to the outputs, as shown in Figure 6, and from different nodes using query mode.

Having identified the outputs and risk probability, the query mode provides information to identify the origin of results, thus providing a way to manage risk. As an example, the company Inditex, that presents the highest *Extreme* risk probability. In Figure 7 it is possible to identify the company selected (red), and the output *Extreme* selected (red), the countries that contribute for this result (suppliers' country of origin), HDI and GSI of these countries. It is possible to identify that 59.01% of this result *Extreme,* is related to countries with HDI between 0.800 and 0.900, 21.95% related to HDI between 0.600 and 0.700 and 6.11% related to HDI between 0.500 and 0.600. It is also important to emphasize that in this case, non-compliances are mainly related to Labour Condition (61.09%) and Human Rights (37.67%).

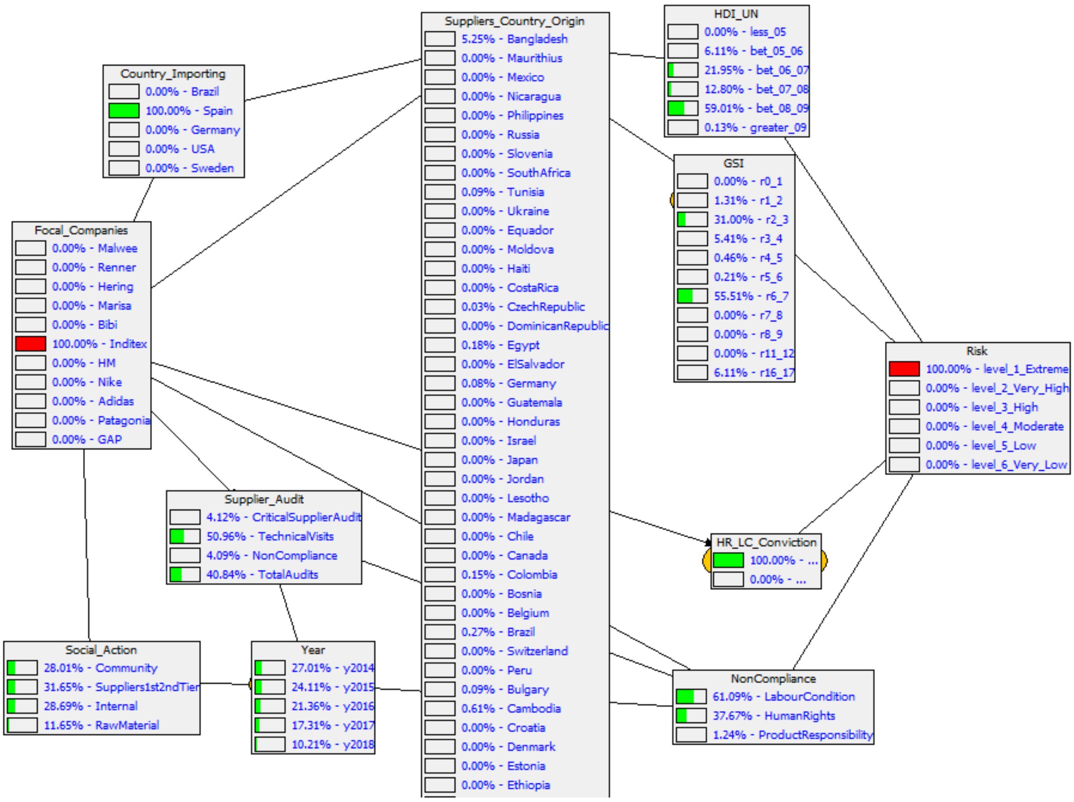


Figure 7 - Results of risk probability inferences identifying *Extreme* risk level

Selecting the lowest HDI, in Figure 8 it is possible to identify the suppliers' countries, Pakistan (90.0%) and Cambodia (10.0%). These two countries present High GSI = 16.8, the highest index in this model. Even though these two countries represent a small percentage of suppliers (Cambodia 0.34% and Pakistan 3,04%), the impact of non-compliance is high. An action plan to prevent possible violations of human rights and working conditions is necessary. As an example is the implementation of the Wage Management System in a supplier factory in Turkey and In Vietnam, awareness training for suppliers on forced labour and modern slavery with IOM, by the H&M company. To identify the social risk probability level and explore the data that influences the outputs, makes it possible to identify the main fragilities and take actions to reduce the risk. Even in a low risk probability, Human Rights violation has high impact for companies and communities. In this case, non-compliances related to Labour Condition (73.39%) have increased, and Human Rights decreased (24.44%). What is an acceptable risk for companies can represent an unmeasurable loss for workers. In several cases, it represents a loss of freedom, health, and quality of life.

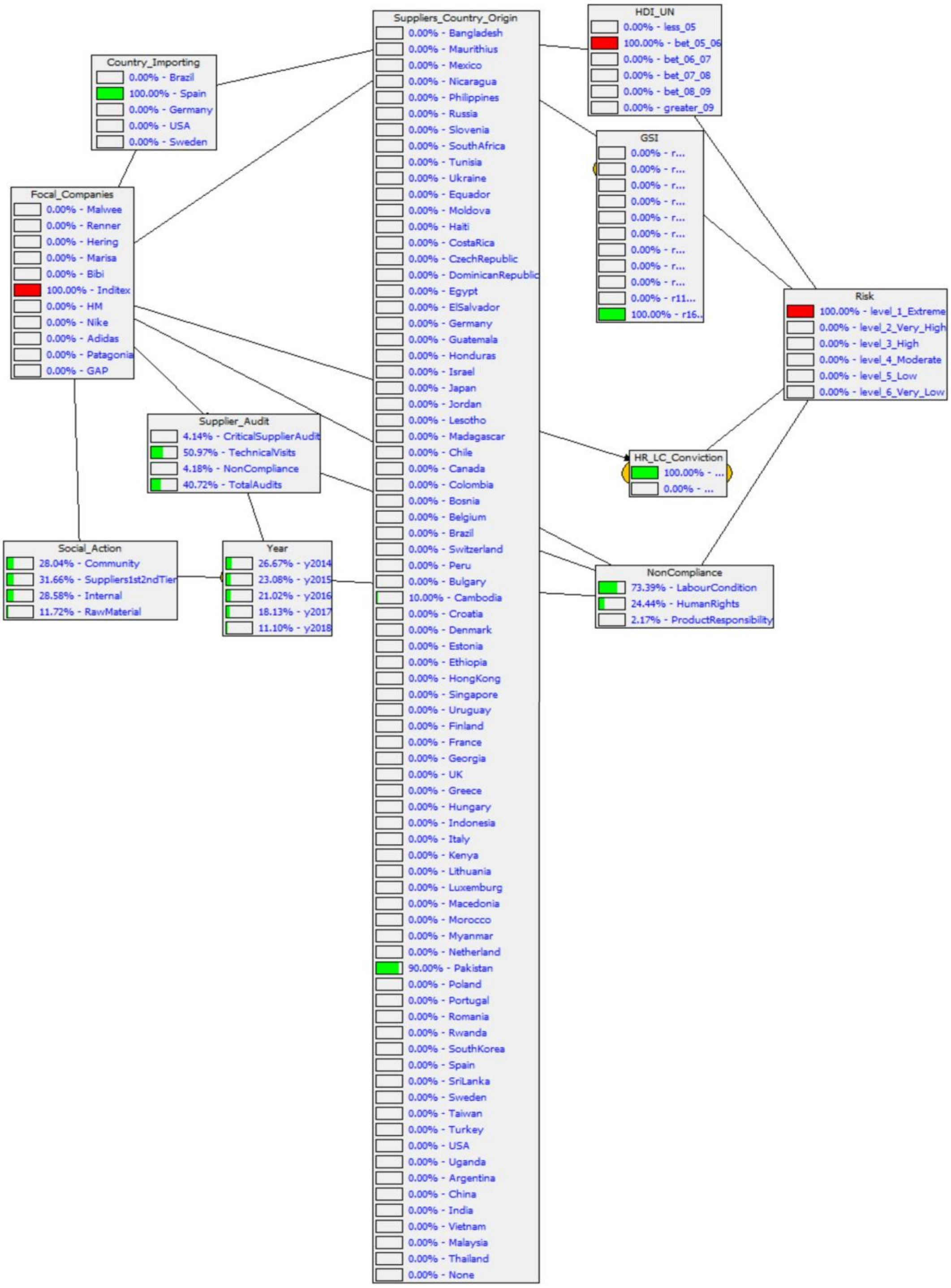


Figure 8 - Results of risk probability inferences selecting *Extreme* level and low HDI

Considering the *Low* risk probability level in the same company, that represents 3.66% (see Figure 6) it is possible to identify the HDI and GSI distribution, in Figure 9, that presents 39.95% of suppliers from countries with HDI between 0.600 and 0.700, 23,18% of countries with HDI between 0.800 and 0.900. Even so, these suppliers come, in 43.26% of cases, from countries with GSI between 6.0 and 7.0, and

36.50% GSI between 2.0 and 3.0. It may be underrepresented, but considering the business ethic, it is crucial to consider the responsibility of the focal companies over the production process, being in line with its CSR and sustainability policies (Luque and Herrero-García, 2019).

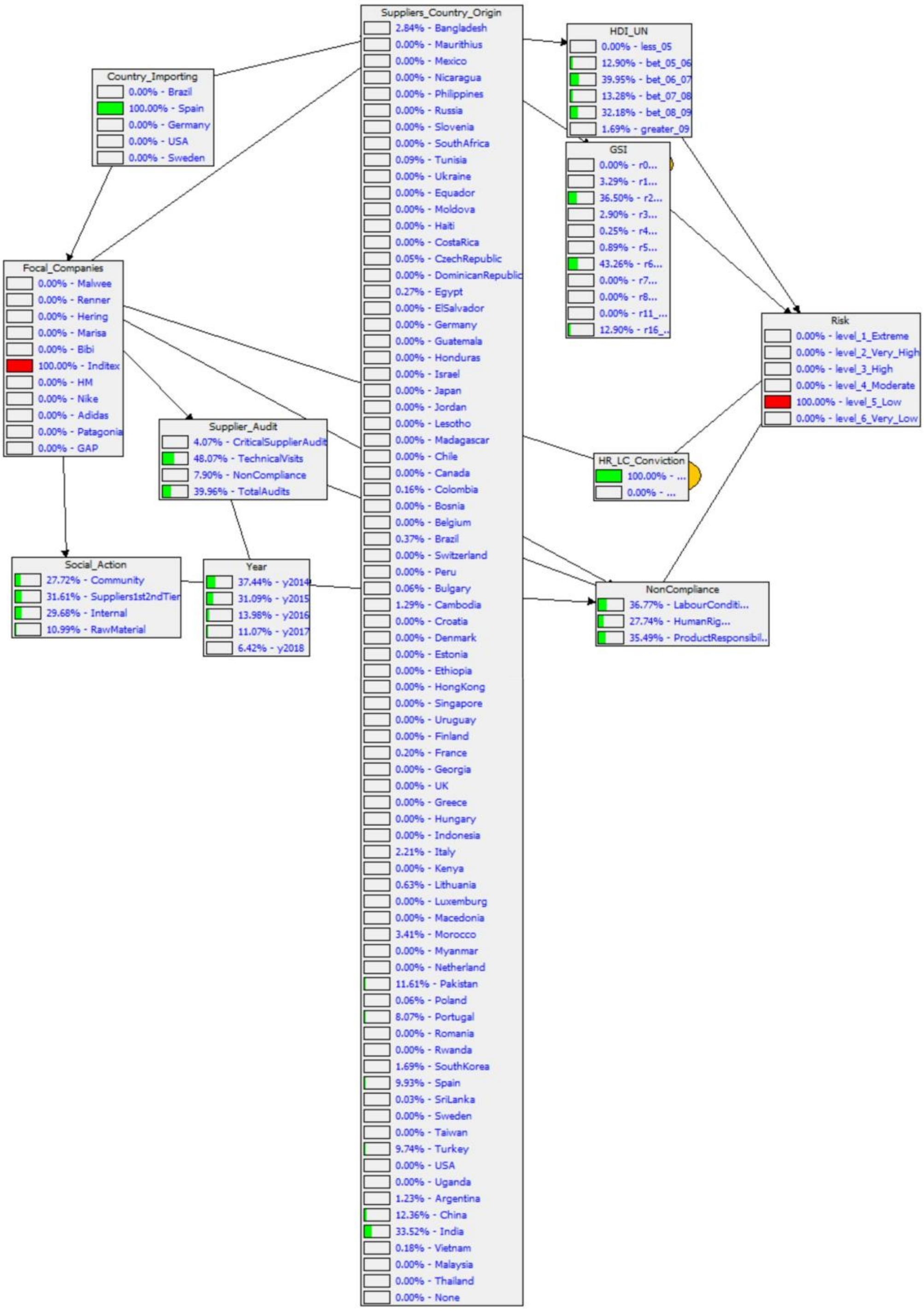


Figure 9 - Results of risk probability inferences identifying *Low* level of risk probability

From this data, it is possible to identify that all nodes change when specific nodes are selected. This is useful and one of the benefits of this model to identify specific characteristics to analyse. For example, if selecting only one random country, in this case, Madagascar (see Figure 10), it is possible to identify that it is Adidas' supplier, presents Low HDI (between 0.500 and 0600) and High GSI (between 7.0 and 8.0). It is a country with *High* risk probability given their characteristics, and it is possible to identify the distribution in the “risk” node. The influence of different nodes of the historical data from companies, like audits, social actions, conviction and non-compliances, also influence the risk probability. The measures to mitigate risk, like increasing audits and social actions in different tiers of suppliers and communities, may explain the *Moderate* (29.35%)*, Low* (21.38%) and *Very Low* (8.90%) risk index.

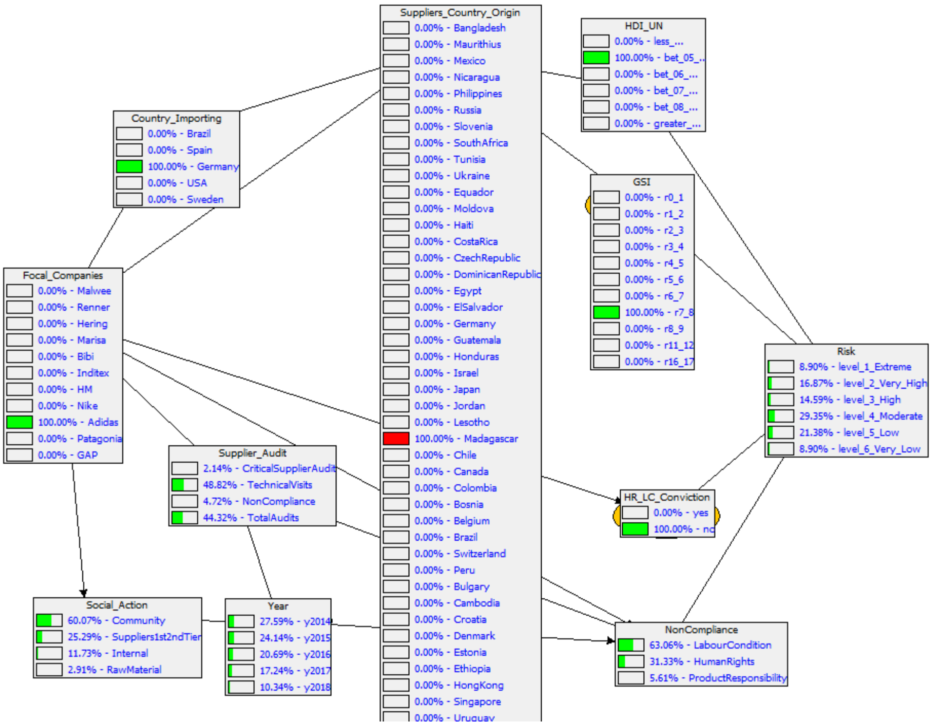


Figure 10 - Results of risk probability inferences identifying a random *country* (Madagascar)

In this BN structure, in addition to the suppliers’ country of origin, the companies’ historical data over five years was used. Companies that have experienced non-compliance issues may be likely to hire a risk supplier. However, the history of corrective actions is also considered in the study because the change in corporate practices may decrease the risk of recurrence, as they increase control, thus decreasing the risk probability. As an example, the company Inditex reported that 8% of social audits in 2018 required corrective actions for non-compliance, mainly in occupational health and safety. As examples of risk mitigation actions are the increasing number of audits, the changes in the process, greater rigour in audits, expansion of the audit's scope for subcontracts, being more productive or even changing the rigour in compliance criteria and the increase in items audited. As stated by Huq et al., (2014) and Aßlander et al. (2016) audits are not enough because Human Rights and Labour Condition violations are not always visible, especially considering that audits are often announced, as informed by companies in sustainability reports (e.g., Hering, 2018; Malwee, 2018; Adidas, 2018; Nike, 2018). When the risk origin can be identified it is necessaire to act proactively and in collaboration with suppliers and stakeholders, especially those who have a close relationship and knowledge of culture and local problems.

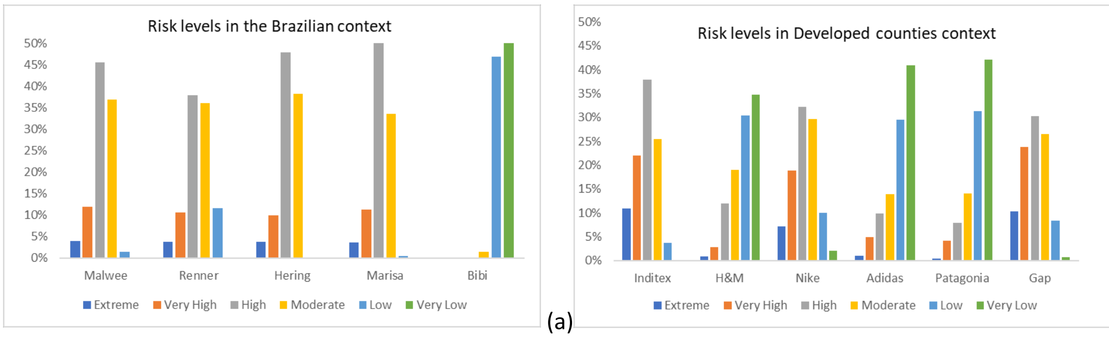
As identified in section 2.1, most models and applications presented in the literature use data from different sources, but to solve a specific or local problem in the supply chain or one tier of suppliers. In this model, we seek to integrate different tiers with external information. Based on internal information, external information was integrated, which in some cases may contradict company information. For example, the company Renner that inform that there are no non-compliances in their international suppliers, but do not disclose which are the international suppliers. We know, through web content mining, that some products come from Bangladesh, which is a country with a high incidence of forced labour (GSI = 3.7), exhaustive working hours, inadequate work conditions and child labour. The probability of non-compliance in the international supply chain can be high, especially since the company reports inform that do not audit 100% of such suppliers, only documental audits, which are sent by mail or e-mail. A lack of transparency and missing data along the supply chain, as well as the inadequate laws and protection systems, especially in developing countries, makes it hard to detect abuses and irregular situations such as slave-like conditions, one of the most severe violations of human rights and labour conditions (Gold et al., 2015).

5.4. Comparison of the BN results

The BN model considers a set of data related to the apparel sector from eleven focal companies, six from developed countries and five from Brazil, a developing country. Using this model, it is possible to compare the risk probability in both contexts, as shown in Figure 11. The results indicate that Brazilian companies present higher risk probability when compared with companies from developed countries, except Bibi, that present very low-risk probability. The distribution of social risk probability levels in companies from developed countries can be explained by the supply chain characteristics and social sustainability strategy, as already addressed by Bubicz et al. (2020a) and Bubicz et al. (2020b).

As Brazilian companies present a high number of local suppliers and social actions are mainly in internal context and local communities, the results are following these characteristics, as well as historical data, GSI and HDI. Also, international suppliers influence this result in the Brazilian context, being a large proportion of suppliers coming from countries with high GSI and low HDI. When a company buys from a country with high GSI, the risk increases. This is in line with studies developed by Zimmer et al. (2017) for risk assessment and Sarkis et al. (2015) for supplier selection, considering social indicators.

In a careful analysis, it is possible to see the influences on this result from buyer' countries characteristics, because the joint probability distribution considers all data from buyers and suppliers to the outputs. Developed countries with high HDI and high GSI are an important parameter to compare, given the historical data. For example, countries like Germany (GSI = 2.0 and HDI = 0,939), Spain (GSI = 2.3 and HDI = 0.893) and Sweden (GSI = 1.7 and HDI = 0,937) have the GSI and HDI higher than Brazil (GSI = 1.8 and HDI = 0,761) (see Appendix 3) however, the risk probability in companies from these countries is lower. In developed countries scenario, the maximum risk probability for the level *Very High* is 23,85% (GAP), level *High* is 37,08% (Inditex), and level *Moderate* is 29,74% (Nike). In the Brazilian context, the maximum risk probability for the level *Very High* is 11,93% (Malwee), level *High* is 51,04% (Marisa), and level *Moderate* is 38,28% (Hering). Supply chain characteristics and social sustainability strategies, already compared in Bubicz et al. (2020b) - section 5, may explain these results. In companies from developed countries, the audits and social sustainability actions cover all tiers of suppliers, and the disclosure is higher and detailed (see Bubicz et al. (2020a) - section 4). In the Brazilian companies, social actions are not fully expanded to all SC tiers to keep control over the production process, and the data disclosure is lower (see the Bubicz et al. (2020b) - section 4), so the risk probability increases. Only company Bibi is highlighted in *Low* and *Very Low* risk probability, being the only one with full vertical integration and total control over the production process from raw material.



(b)

Figure 11 – Risk probabilities levels by companies compared by Brazilian context (a) and developed countries (b).

5.5. Missing data

Several factors influence risk. This proposed model is a sample of what is possible to do, however, there is a data limitation, using only the complete data available of the eleven companies analysed. It is possible to increase the assertiveness of the analysis by inserting more specific data and adding new sources. Having these limitations in mind it is essential to note that the model was built combining real data available and the scientific knowledge of the author to develop the structure, but is a first attempt to analyse this problem and not an end.

For greater accuracy, it would be necessary to have non-compliance data by country, which would make the model more assertive in terms of risk probability. As identified by Bubicz et al. (2020b) the ABVTEX has an important role in Brazilian apparel SC, but its data are not complete and structured by companies to be included in this model. Also, internal data from countries, related to working conditions could be inserted, such as informality index.

In many cases, non-compliance data are indicated in the reports by type and percentages, and not by absolute numbers. This makes it difficult to analyse and identify the amount of non-compliance by type. Likewise, Brazilian companies that do not disclose international suppliers makes it challenging to analyse. For example, the Renner company indicates "*approval of international suppliers in technical visits for social responsibility*" (Renner Sustainability Report, 2018). However, it does not indicate the quantity and the suppliers' country of origin. Yet, the number of international companies audited, in the same sustainability report, "*48% of international resale suppliers audited*", without indicating how many there are.

Finally, the availability of data and the way to treat it may have different results when integrating knowledge of professionals and researchers from different areas. This is also one of the advantages of the model, as it can be improved as new knowledge is integrated, without having to restart the entire process. Model auditing processes must be performed by professionals with experience in BN models, to validate the structure avoiding data manipulation.

5.6. Study limitations and future directions

Sustainability is currently a major concern in all companies analysed. The social dimension has been widely addressed and is a part of companies' strategy and action plans. Social concerns are interrelated with risk management as identified in the sustainability reports and standards and are closely monitored by companies across different tiers of suppliers along the supply chain. The lack of transparency has been identified as one of the main problems and needs to be addressed and solved, being a way to reduce Human Rights and Labour Conditions violations, and negative impacts in the Society, that carries the weight of neglect and carelessness. Responsible Actions are the primary tool to achieve social sustainability when applied with shared responsibility, integrating information and communication technologies to increase transparency and correct the failures. The actions should reduce the pressure for low cost and high profit, that are usually overburdening the different tiers of suppliers, especially in raw material extraction and in the first production processes.

Sustainability must be a commitment of all entities involved in the apparel supply chain, from the raw material production to the consumer, who must also be an agent for fashion circularity (Hofmann and Jaeger-Erben, 2020). Considering the importance of the focal companies in this supply chain, they were the ones analysed.

One of the study limitations is the non-consideration of multi-brand retailers. They should be included in future research, as they also have responsibility for the products they sell as well as its origin. Another limitation of the study is the use of upstream data only, given that there is still little investigation of the social impacts from consumption to the end-of-life, and this would improve the performance of the model. Even the companies analysed are large players, the universe of eleven companies is a small sample of the apparel sector. By increasing the sample, it is also possible to integrate other types of information and, consequently, improve the model. Finally, the analysis of companies from Brazil shows the characteristics of only one developing country, which does not represent the reality of the different countries in which most suppliers are located.

Additionally, and considering the limitations, it is important to expand the model to increase strategic information and thus, to integrate suppliers from developing countries, with Low HDI and high SGI, having a look at the fragilities and expanding the historical data. Furthermore, it is essential to apply the developed model in real sets to further understand its limitation and correct then, and thus, build a more comprehensive model allowing the BN development and providing further analysis and improvement. Improvement should also integrate information from all SC entities and expanding the data of external stakeholders that influence this SC, thus providing better management of the social dimension of sustainability (Jakhar et al., 2020). Also, it is crucial to increase the scientific knowledge and integrate social sustainability dimension in the sale process and after-sales. There are few approaches to outbound sustainability, from post-sales, in the literature, being more related to environmental issues (Silva et al., 2018) and consumer perceptions (Garcia et al., 2019). It is necessary to extend the studies to understand the implications of social sustainability from sales and post-consumption in a holistic way, to close the loop and achieve circular fashion. This Bayesian Network may integrate this information, and thus have a broad vision for social management of sustainability in an integrated manner, with the different entities and stakeholders involved directly and indirectly in the apparel supply chain, as shown in Figure 12.

Figure 12 – Social sustainability management model development and the next three main steps for the future using a BN model

6. Conclusion

The social dimension of sustainability has been addressed in the last years, being a constant concern in the companies and the scientific community. Human Right, Labour Condition, Society and Product Responsibility are the four aspects of social sustainability dimension in the strategic management focus in the apparel supply chain. However, there are still no answers on how to solve the non-compliance gaps or how to prevent it so as to pursue social sustainability. In this study, an Artificial Intelligence model is presented as a way to help managers and practitioners to understand better where the main problems exist and, thus, to act proactively.

Artificial Intelligence for the social dimension of sustainability is still in an early stage in research (Min, 2010) and this study may contribute with knowledge, providing a first attempt model to manage the social dimension with stakeholders collaboration, providing an analysis with the inclusion of an external set of data. Using the SamIam software, a Bayesian Network was developed, based on AI mechanisms, that provide a risk probability level. It is intended to be useful and easy to use so as to support the management of the social dimension in the apparel sector. Management tools are usually related to mathematical models that are difficult to understand and often require deep knowledge, as well as highly trained professionals. In this model, managers and practitioners have a model with a graphical interface that is easy to understand and the visual information of the responses of the algorithm is also presented clearly without the need to interpret mathematical models. From the data insertion e and the correct identification of the influence and relationship between the nodes (a step that requires a thorough analysis by several specialists and decision-makers), the information is processed quickly, clearly, and, mainly, usefully.

From this BN, the information can be managed in different ways, identifying the relationship between nodes that contribute to identifying risk probability. From these outputs and answering queries, managers and practitioners can make decisions and effective measures to manage the main fragilities, minimising risk probability and negative impacts along the supply chain. Furthermore, AI can provide greater transparency of operations and, consequently, better management and control.

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Appendix 1 - Companies data for Bayesian Network model

1.a – Companies data of the developed countries, from 2014 to 2018

	Company data	Year				
		2014	2015	2016	2017	2018
Adidas	Total Suppliers	1133	1079	1038	782	806
	Local Suppliers	21	19	13	13	13
	Sub-contractors *	132	132	131	130	131
	Abroad **	1112	1060	1025	769	793
	Audits*	1193	1135	989	1015	1207
	Critical suppliers audit***	104	39	31	42	39
	Audit international supplier	1182	1116	1033	1015	1194
	Technical visits - contractors and subcontractors ****	1320	1255	1226	1241	1207
	Non-compliance	274	40	78	79	95
	Social Projects (total)	1039	968	476	409	525
GAP	Total Suppliers	1083	1003	933	855	778
	Local Suppliers	4	4	4	3	3
	Sub-contractors *	372	646	279	179	194
	Abroad **	1079	999	929	852	775
	Audits*	968	1079	1038	773	778
	Critical suppliers audit***	181	172	160	144	105
	Audit international supplier	968	999	999	852	775
	Technical visits - contractors and subcontractors ****	1000	1079	1038	773	778
	Non-compliance	284	241	238	257	188
	Social Projects (total)	18	13	16	28	41
H&M	Total Suppliers	850	820	1298	1230	1234
	Local Suppliers	18	15	15	15	15
	Sub-contractors *	261	307	287	320	347
	Abroad **	832	805	1283	1215	1219
	Audits*	2268	1300	1247	1589	1430
	Critical suppliers audit***	30	25	26	27	12
	Audit international supplier	1355	1283	1246	1860	1415
	Technical visits - contractors and subcontractors ****	3623	3556	1247	1736	1430
	Non-compliance	30	33	39	41	47
	Social Projects (total)	28	19	16	15	18
Inditex	Total Suppliers	1625	1725	1805	1824	1866
	Local Suppliers	216	229	208	198	186
	Sub-contractors *	NI	NI	NI	NI	NI
	Abroad **	1409	1496	1597	2159	1680
	Audits*	2029	2703	2302	2552	2546
	Critical suppliers audit***	248	207	183	255	417
	Audit international supplier	1813	2474	2302	2223	1982
	Technical visits - contractors and subcontractors ****	2367	2800	4011	2252	5359
	Non-compliance	257	325	194	263	160
	Social Projects (total)	460	456	519	594	622
Nike	Total Suppliers	719	692	663	591	594
	Local Suppliers	63	58	56	50	42
	Sub-contractors *	180	176	125	108	104
	Abroad **	656	634	607	541	552
	Audits*	685	654	576	406	471
	Critical suppliers audit***	460	354	121	86	92
	Audit international supplier	680	680	404	337	335
	Technical visits - contractors and subcontractors ****	1300	1300	1200	1200	1200
	Non-compliance	85	86	82	91	85
	Social Projects (total)	70	75	78	78	82
Patagonia	Total Suppliers	80	80	80	80	81
	Local Suppliers	12	12	11	11	9
	Sub-contractors *	21	21	21	21	21
	Abroad **	69	69	69	69	72
	Audits*	85	85	81	81	81
	Critical suppliers audit***	12	12	12	12	8
	Audit international supplier	80	80	80	80	80
	Technical visits - contractors and subcontractors ****	125	125	125	125	125
	Non-compliance	15	12	12	12	8
	Social Projects (total)	80	82	82	85	92

*contractors from certified suppliers
**International suppliers are only audited on demand, in cases of complaints about social issues, and if noncompliance is found, the supplier is de-accredited.
***Compliance Audit of Social Responsibility
**** The visits made to subcontractors who had been denied access - these companies are counted as "high risk".
NI = Not Informed

1.b – Companies data of Brazil, from 2014 to 2018

Company data		Year				
		2014	2015	2016	2017	2018
Renner	Total Suppliers	530	456	460	497	525
	Local Suppliers	330	256	256	256	290
	Sub-contractors *	NI	1162	985	960	985
	Abroad **	200	200	204	200	195
	Audits	1128	3129	3925	3595	4394
	Critical suppliers audit***	0	39	62	78	87
	Audit international supplier	0	0	0	112	93
	Technical visits - contractors and subcontractors ****	1768	2297	3925	3595	2707
	Non-compliance	0	0	0	0	126
	Social Projects (total)	174	180	84	58	51
Hering	Total Suppliers	1034	1160	1475	3021	2896
	Local Suppliers	878	1099	1373	2921	2835
	Sub-contractors *	26	30	79	71	46
	Abroad **	60	61	102	100	61
	Audits	664	718	588	587	469
	Critical suppliers audit***	62	52	53	365	330
	Audit international supplier	0	0	0	0	0
	Technical visits - contractors and subcontractors ****	1729	1871	1527	1602	1600
	Non-compliance	0	0	0	365	330
	Social Projects (total)	40	43	30	42	42
Marisa	Total Suppliers	314	314	314	314	243
	Local Suppliers	256	256	256	256	200
	Sub-contractors *	1200	1200	1200	1200	1154
	Abroad **	58	58	58	58	43
	Audits	2824	2824	3203	1638	2204
	Critical suppliers audit***	296	173	179	183	170
	Audit international supplier	58	58	58	58	43
	Technical visits - contractors and subcontractors ****	2824	2824	3203	1638	2204
	Non-compliance	0	0	0	0	0
	Social Projects (total)	2	2	2	3	3
Malwee	Total Suppliers	3021	3364	1742	1742	1740
	Local Suppliers	2747	3129	1552	1552	1550
	Sub-contractors *	35	45	147	163	163
	Abroad **	274	235	190	190	190
	Audits	1675	3129	1408	1408	1325
	Critical suppliers audit***	12	0	4	211	118
	Audit international supplier	0	0	0	0	0
	Technical visits - contractors and subcontractors ****	1675	3129	1408	1408	1320
	Non-compliance	0	0	4	6	5
	Social Projects (total)	28	19	21	17	21
Bibi	Total Suppliers	363	363	363	363	364
	Local Suppliers	302	304	316	316	337
	Sub-contractors *	NI	NI	NI	NI	NI
	Abroad **	61	59	47	47	48
	Audits	363	363	363	363	363
	Critical suppliers audit***	3	5	4	2	3
	Audit international supplier	0	0	0	0	0
	Technical visits - contractors and subcontractors ****	5	3	8	3	6
	Non-compliance	0	0	0	0	0
	Social Projects (total)	9	12	10	12	12

*contractors from certified suppliers
**International suppliers are only audited on demand, in cases of complaints about social issues, and if non-compliance is found, the supplier is de-accredited.
***Compliance Audit of Social Responsibility
**** The visits made to subcontractors who had been denied access - these companies are counted as "high risk".
*****ABVTEX Certification include local suppliers and sub-suppliers
NI = Not Informed

Appendix 2 – Suppliers country of origin based on suppliers list information and reports of the eleven companies analysed.

Adidas	**Nike**	**Inditex**	**GAP**	**H&M**	**Patagonia**	**Malwe**	**Hering**	**Marisa**	**Bibi**	**Renner**
551 factories	525 factories	1449 factories	707 factories	655 factories	102 factories	4 own factories	11 own factories		2 own factories	
706,000 workers	1,052,195 workers	2 million workers	1 million workers	930,000 workers	78,000 workers	5500 workers	6189 workers	12344 workers	1174 workers	22334 workers
52 countries	40 countries	23 countries	25 countries	41 countries						
Argentina	Argentina	Argentina	Bangladesh	Bangladesh	Bangladesh	Brazil	Brazil	Brazil	Brazil	Brazil
Bangladesh	Bosnia and Herzegovina	Bangladesh	Cambodia	Bulgaria	China	China	China	China	China	China
Belgium	Brazil	Bulgaria	China	Cambodia	Colombia	Bangladesh	Bangladesh	Uruguay	Other NI	Bangladesh
Bosnia and Hezergovina	Bulgaria	Brazil	Colombia	China	El Salvador	Other NI*	India	India		Other NI
Brazil	Cambodia	Cambodia	Dominican Republic	Croatia	India		Other NI	Bangladesh		
Cambodia	Canada	China	Egypt	Czech Republic	Israel			Malaysia		
Canada	China	Czech Republic	El Salvador	Denmark	Japan			Indonesia		
Chile	Croatia	Egypt	Guatemala	Estonia	Jordan			USA		
China	Ecuador	France	Haiti	Ethiopia	Mexico			Other NI		
Colombia	Egypt	Germany	Honduras	Finland	Nicaragua					
Costa Rica	El Salvador	India	India	France	Philippines					
Czech Republic	Georgia	Italy	Indonesia	Georgia	Sri Lanka					
Dominican Republic	Germany	South Korea	Italy	Germany	Taiwan					
Egypt	Greece	Lithuania	Jordan	Great Britain	Thailand					
El Salvador	Guatemala	Morocco	Myanmar	Greece	USA					
Georgia	Honduras	Pakistan	Nicaragua	Hungary	Vietnam					
Germany	India	Poland	Pakistan	India						
Guatemala	Indonesia	Portugal	Philippines	Indonesia						
Honduras	Israel	Spain	Portugal	Italy						
Hungary	Italy	Sri Lanka	South Korea	Kenya						
India	Japan	Tunisia	Sri Lanka	Lithuania						
Indonesia	Jordan	Turkey	Taiwan	Luxembourg						
Israel	Korea (Republic of)	Vietnam	Turkey	Macedonia Fyro						
Italy	Malaysia		USA	Morocco						
Japan	Mexico		Vietnam	Myanmar						
Jordan	Moldova (Republic of)			Netherlands						
South Korea	Netherlands			Pakistan						
Lesotho	Nicaragua			Poland						
Lithuania	Pakistan			Portugal						
Madagascar	Poland			Romania						
Malaysia	Romania			Rwanda						
Mauritius	South Africa			South Korea						
Mexico	Spain			Spain						
Myanmar	Sri Lanka			Sri Lanka						
Nicaragua	Taiwan, Province of China			Sweden						
Pakistan	Thailand			Taiwan						
Philippines	Turkey			Thailand						
Poland	UK			Turkey						
Portugal	USA			USA						
Russia	Viet Nam			Uganda						
Slovenia				Vietnam						
South Africa										
Spain										
Sri Lanka										
Taiwan										
Thailand										
Tunisia										
Turkey										
Ukraine										
UK										
USA										
Vietnam										

Appendix 3 – Global Slavery Index (GSI) and Human Development Index (HDI) per country

Country	GSI (vp 1,000)	HDI-UN
Argentina	1.3	0.830
Bangladesh	3.7	0.614
Belgium	2.0	0.919
Bosnia and Herzegovina	3.4	0.769
Brazil	1.8	0.761
Bulgaria	4.5	0.816
Cambodia	16.8	0.581
Canada	0.5	0.922
Chile	0.8	0.847
China	2.8	0.758
Colombia	2.7	0.761
Costa Rica	1.3	0.794
Croatia	6.0	0.837
Czech Republic	2.9	0.891
Denmark	1.6	0.930
Dominican Republic	4.0	0.745
Ecuador	2.4	0.758
Egypt	5.5	0.700
El Salvador	2.5	0.667
Estonia	3.6	0.882
Ethiopia	6.1	0.470
Finland	1.7	0.925
France	2.0	0.891
Georgia	4.3	0.786
Germany	2.0	0.939
Greece	7.9	0.872
Guatemala	2.9	0.651
Haiti	5.6	0.503
Honduras	3.4	0.623
Hong Kong	1.1	0.939
Hungary	3.7	0.845
India	6.1	0.647
Indonesia	4.7	0.707
Israel	3.9	0.906
Italy	2.4	0.883
Japan	0.3	0.915
Jordan	1.8	0.723
Kenya	6.9	0.579

Country	GSI (vp 1,000)	HDI-UN
Lithuania	5.8	0.869
Luxembourg	1.5	0.909
Macedonia Fyro	8.7	0.759
Madagascar	7.5	0.521
Malaysia	6.9	0.804
Mauritius	1.0	0.796
Mexico	2.7	0.767
Moldova (Republic of)	5.5	0.711
Morocco	2.4	0.676
Myanmar	11.0	0.584
Netherlands	1.8	0.933
Nicaragua	2.9	0.651
Pakistan	16.8	0.560
Peru	2.6	0.759
Philippines	7.7	0.712
Poland	3.4	0.872
Portugal	2.5	0.850
Romania	4.3	0.816
Russia	5.5	0.824
Rwanda	11.6	0.536
Singapore	3.4	0.935
Slovenia	2.2	0.902
South Africa	2.8	0.705
South Korea	1.9	0.906
Spain	2.3	0.893
Sri Lanka	2.1	0.780
Sweden	1.6	0.937
Switzerland	1.7	0.946
Taiwan	0.5	0.885
Thailand	8.9	0.765
Tunisia	2.2	0.739
Turkey	6.5	0.806
Uganda	7.6	0.528
UK	2.1	0.920
Ukraine	6.4	0.750
Uruguay	1.0	0.808
USA	1.3	0.920
Vietnam	4.5	0.693

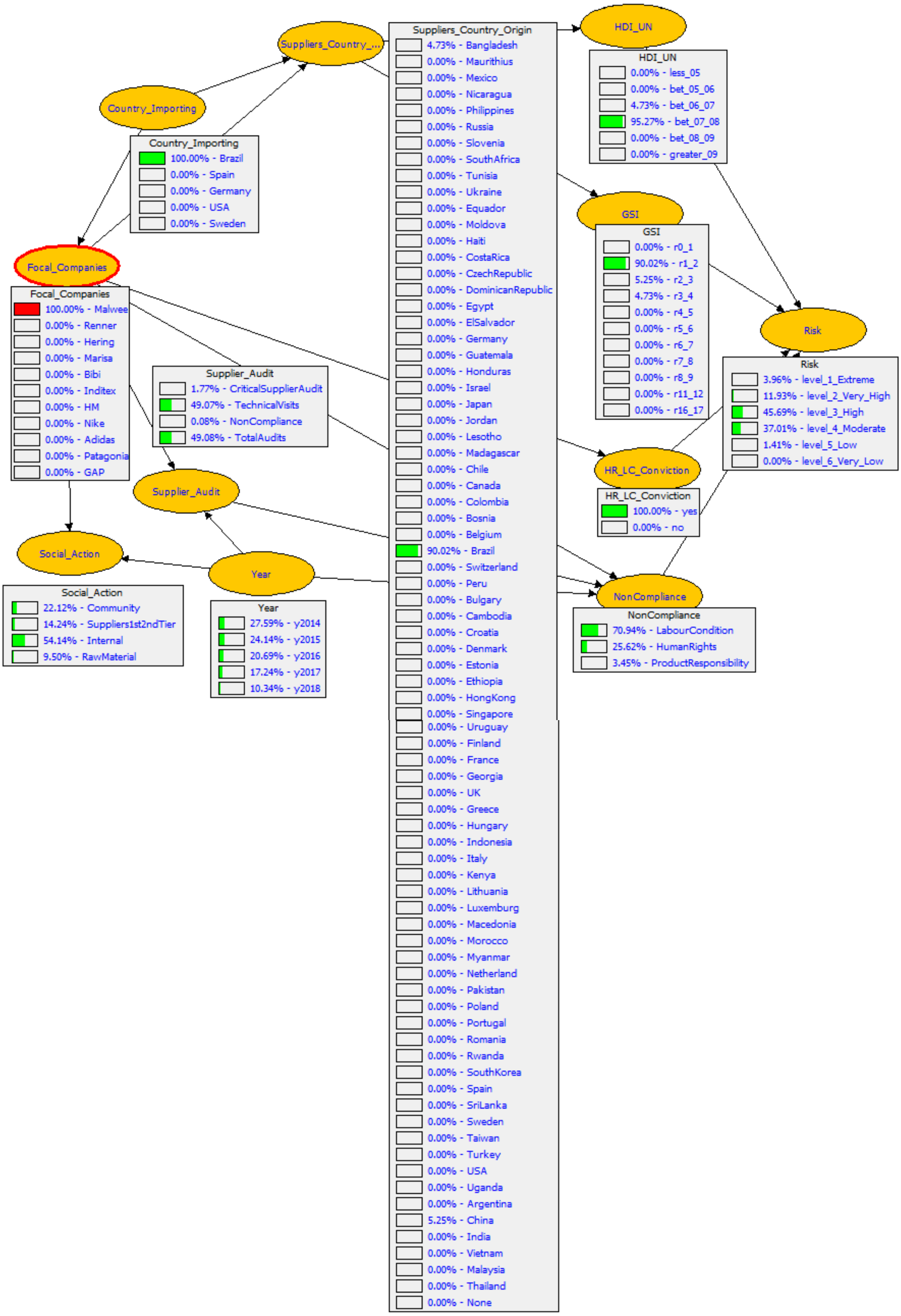
Source of data:

GSI - By Wal Free Foundation - https://www.globalslaveryindex.org/

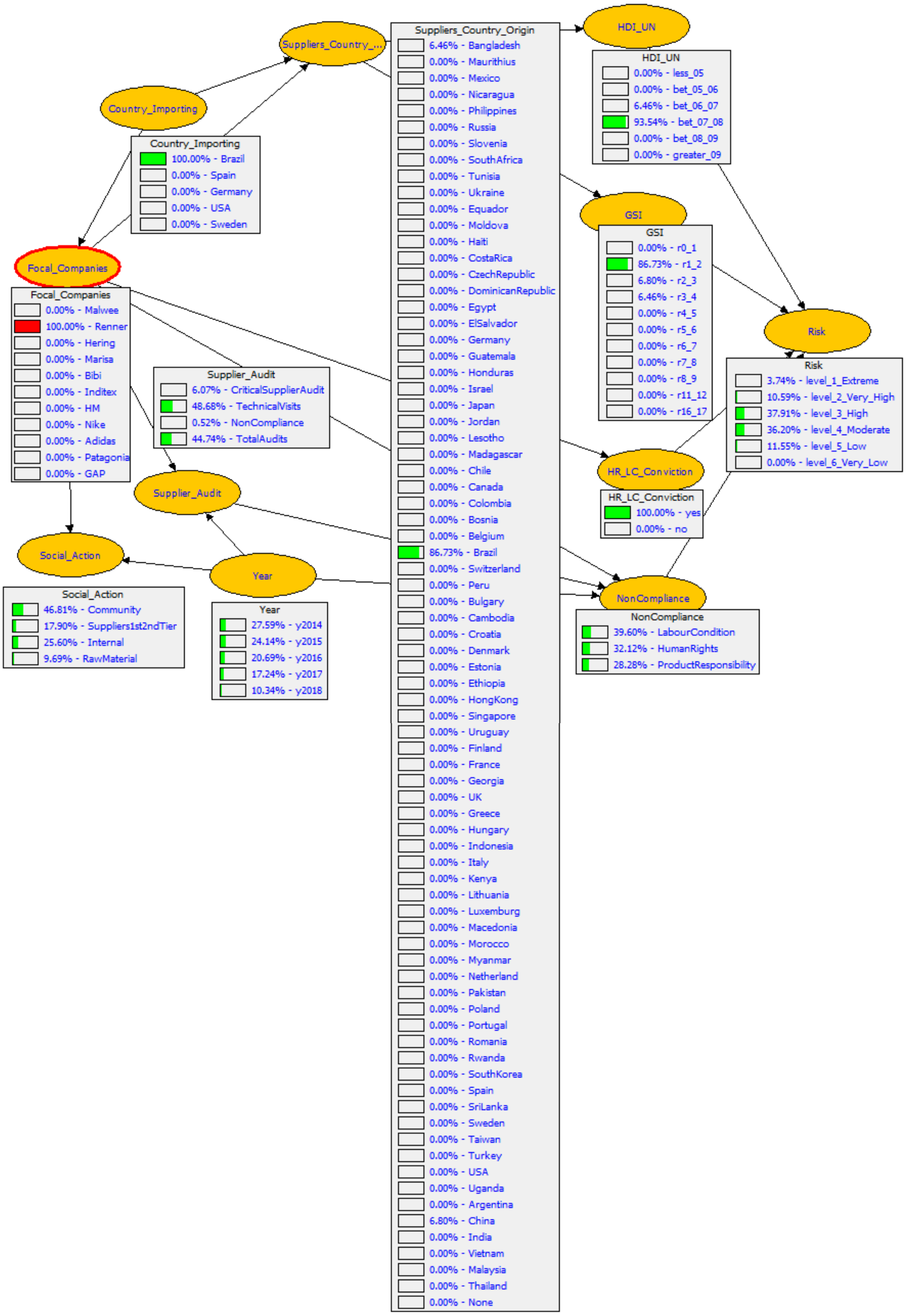
HDI – By United Nations - http://hdr.undp.org/en/content/human-development-index-hdi

Appendix 4 – Results of the BN Risk Probabilities Inferences

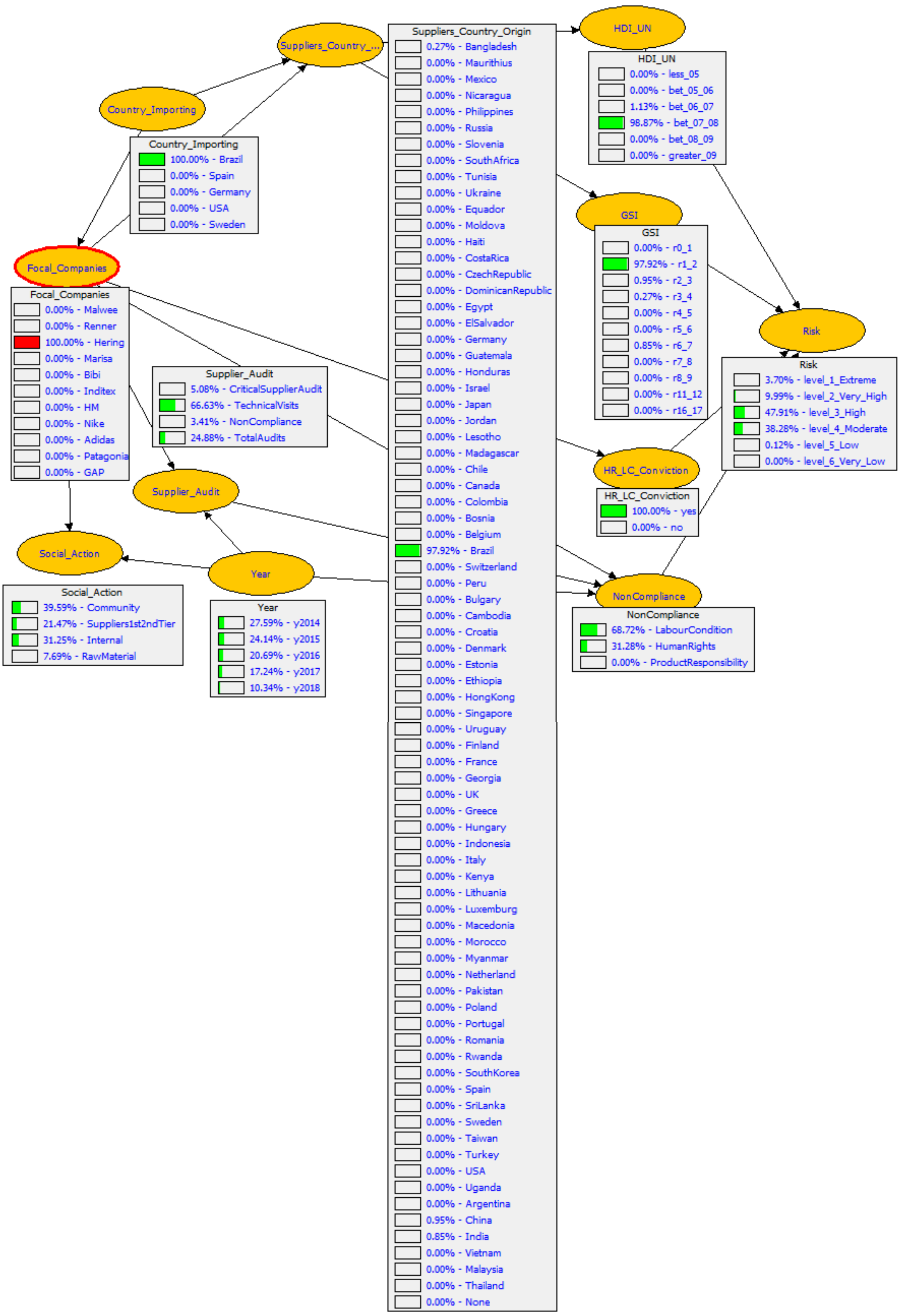
4.1 - Inference of risk probability level for company Malwee



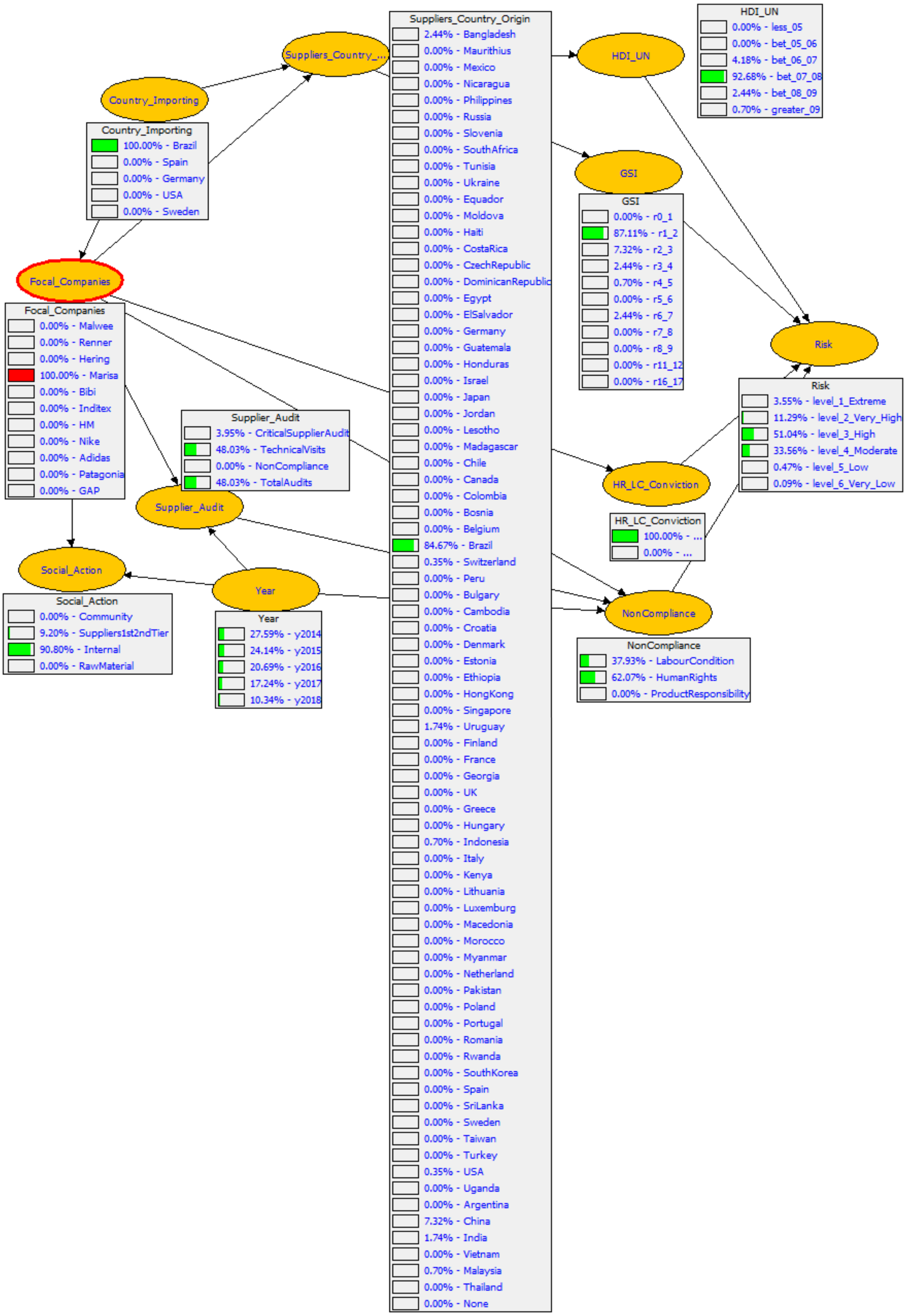
4.2 – Inference of risk probability level for company Renner



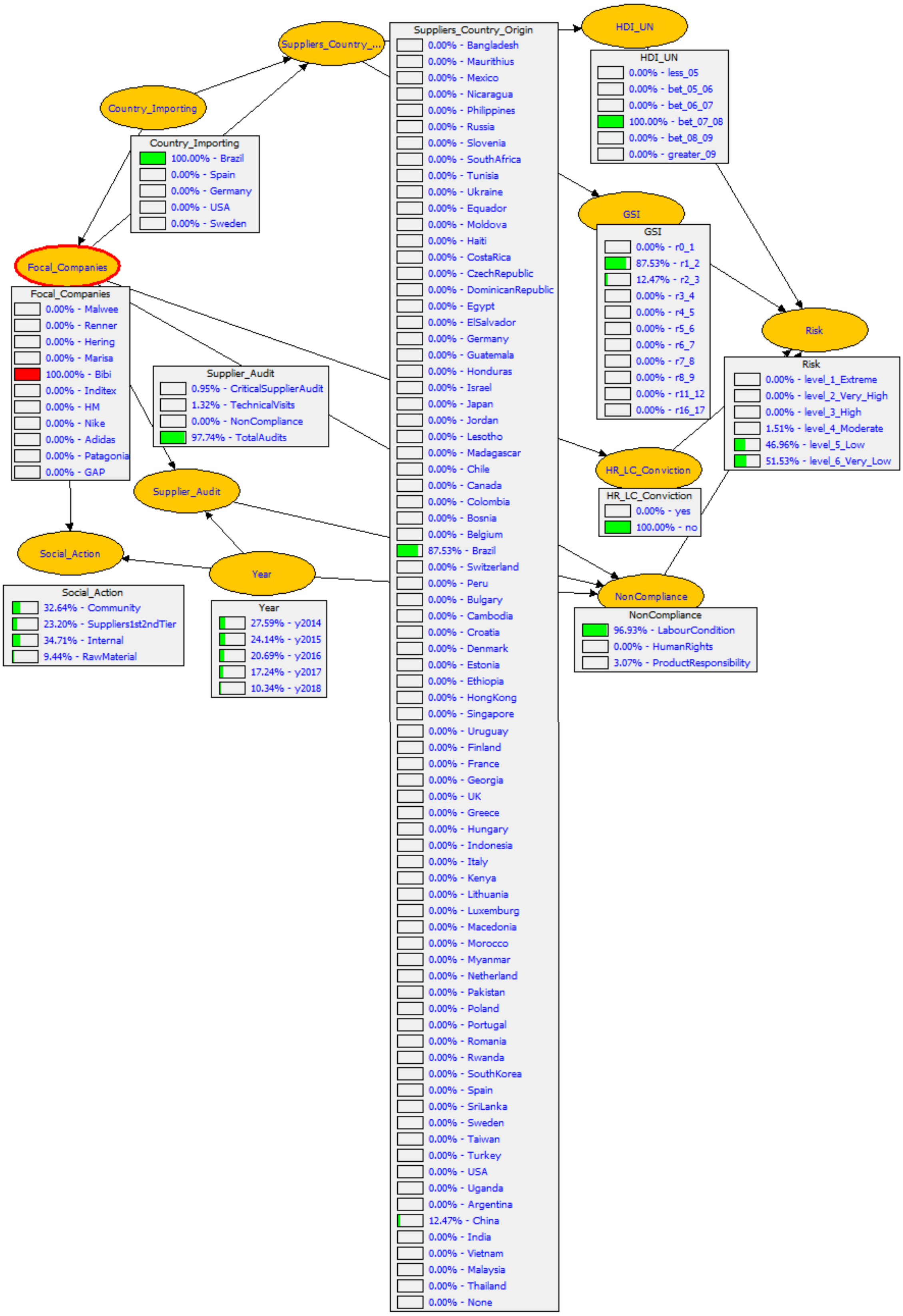
4.3 – Inference of risk probability level for company Hering



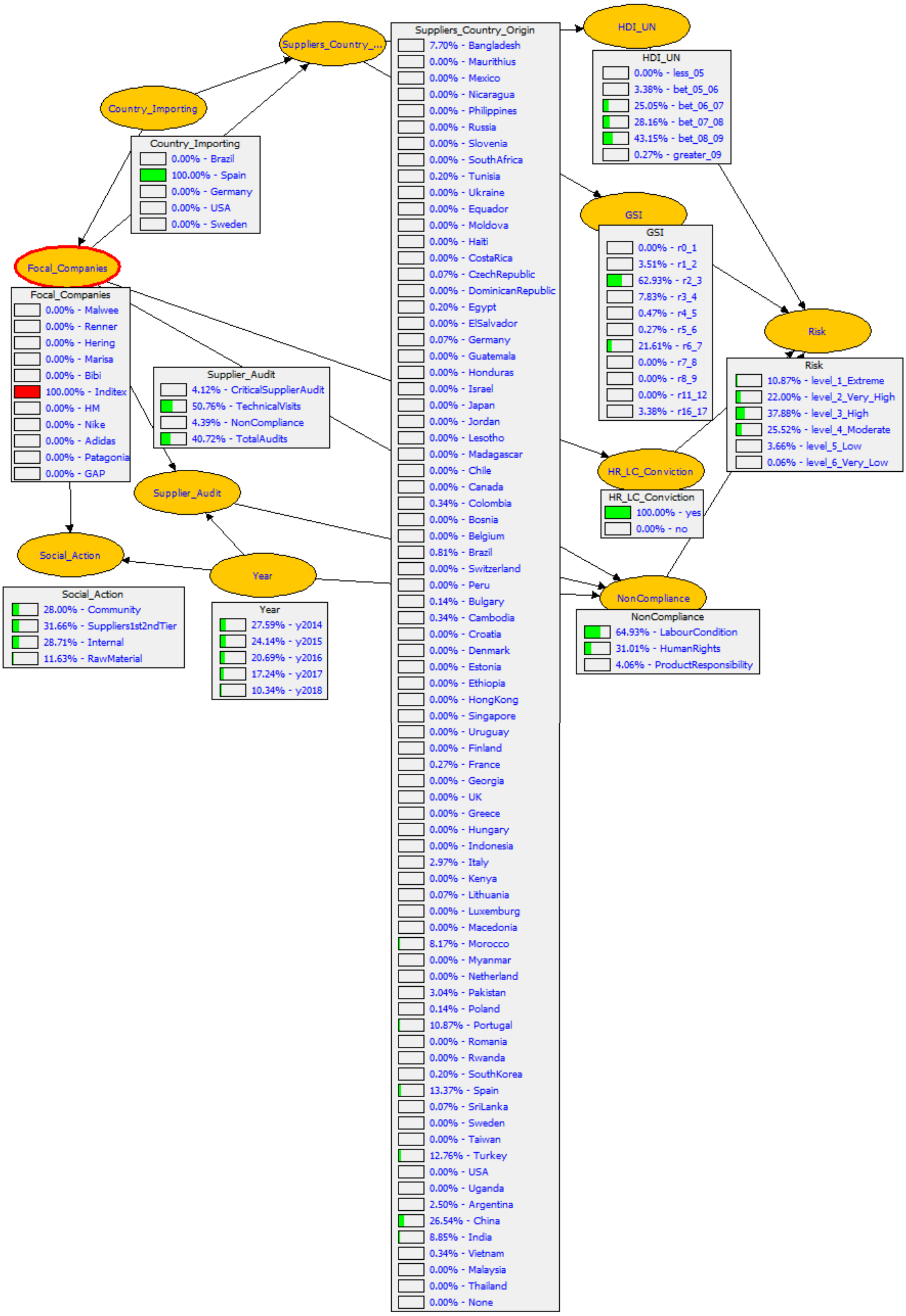
4.4 – Inference of risk probability level for company Marisa



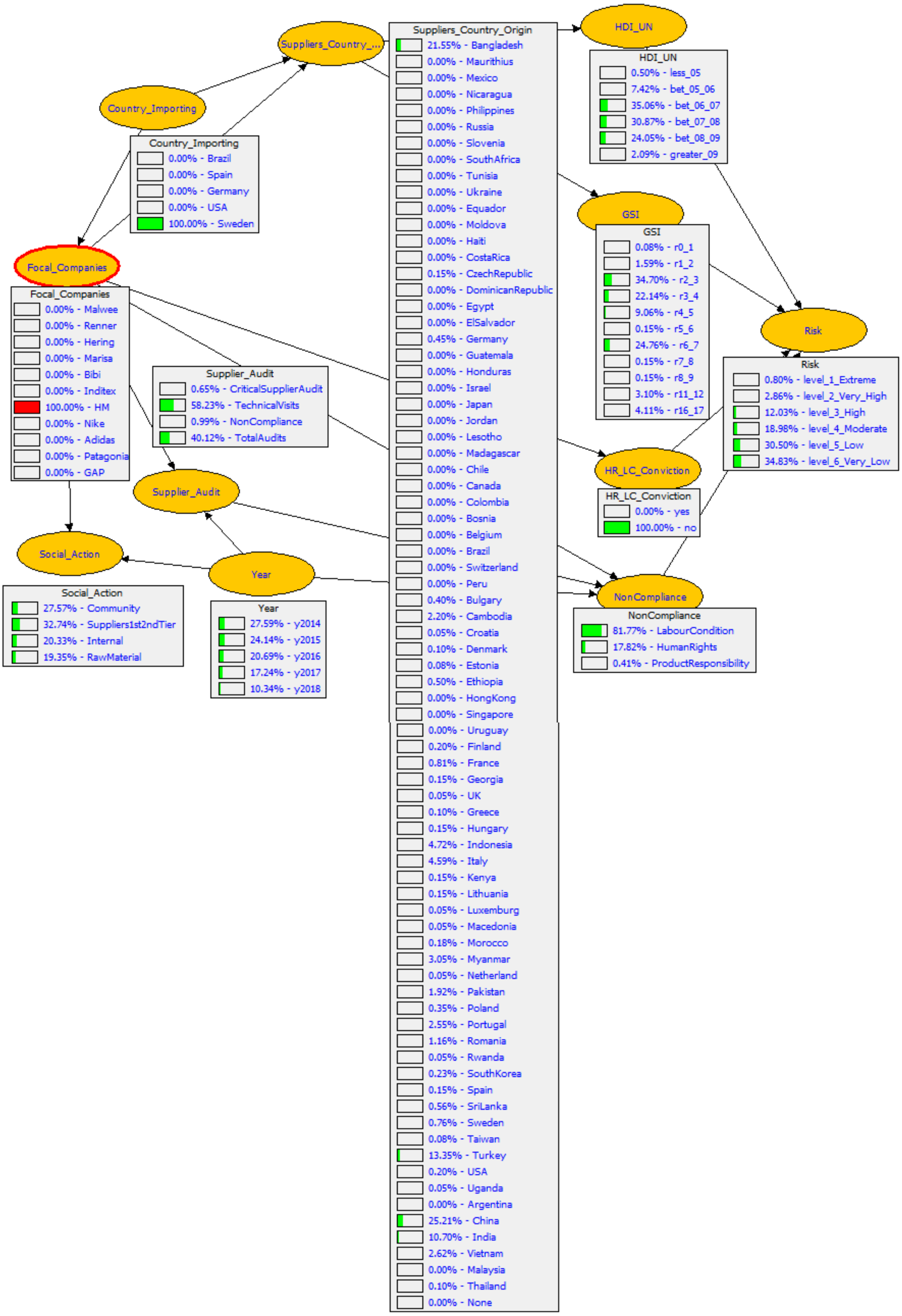
4.5 – Inference of risk probability level for company Bibi



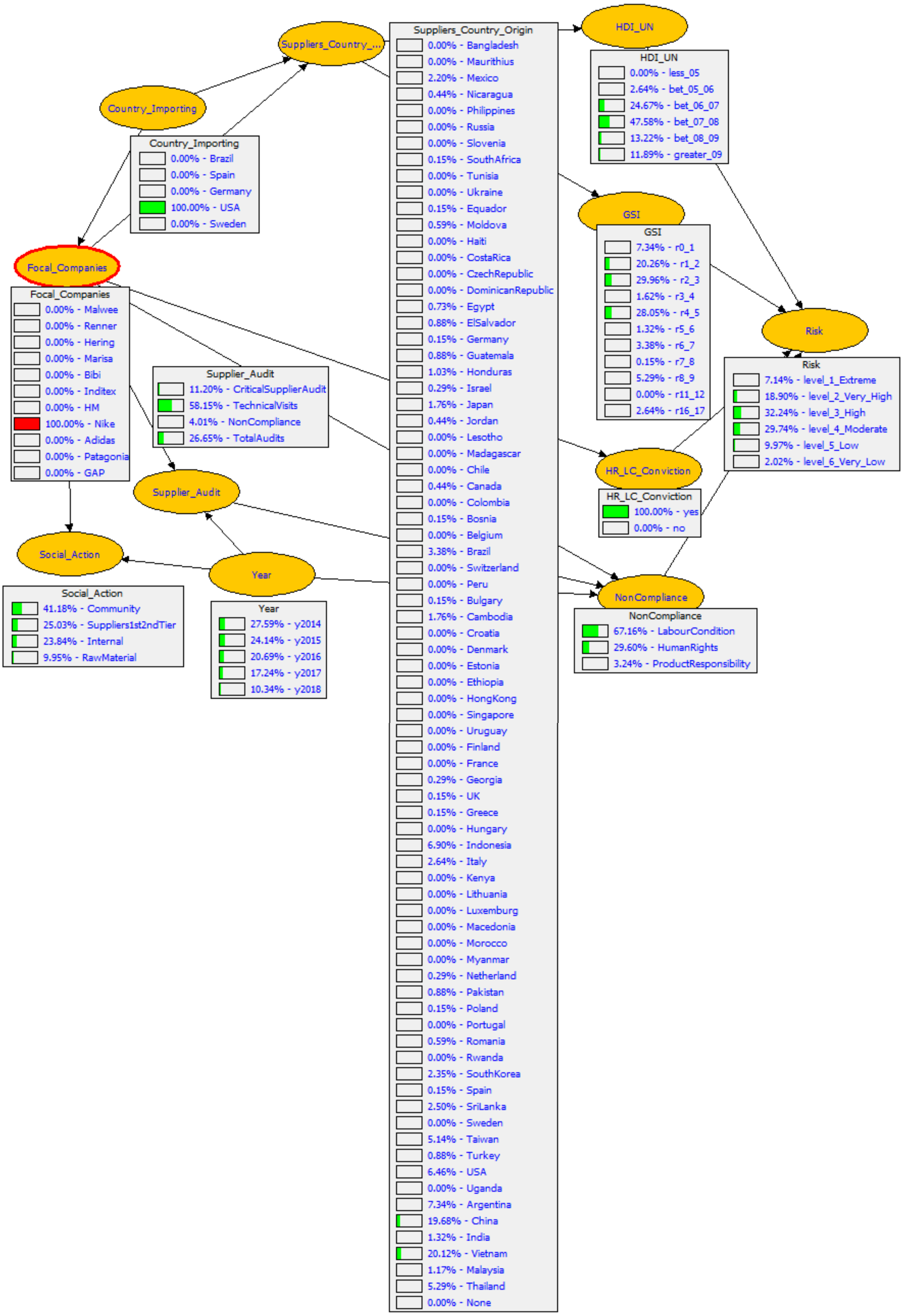
4.6 – Inference of risk probability level for company Inditex



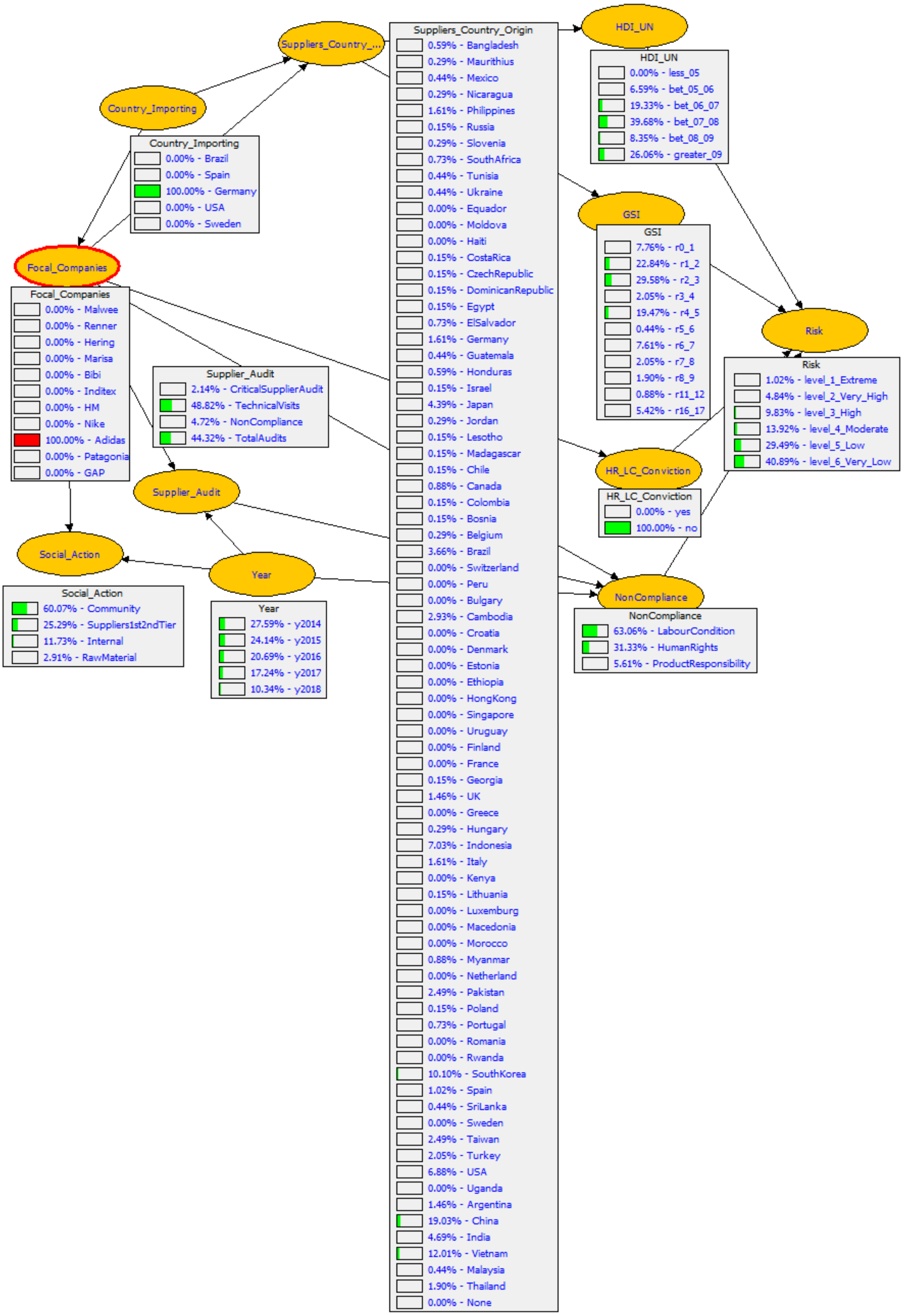
4.7 – Inference of risk probability level for company H&M



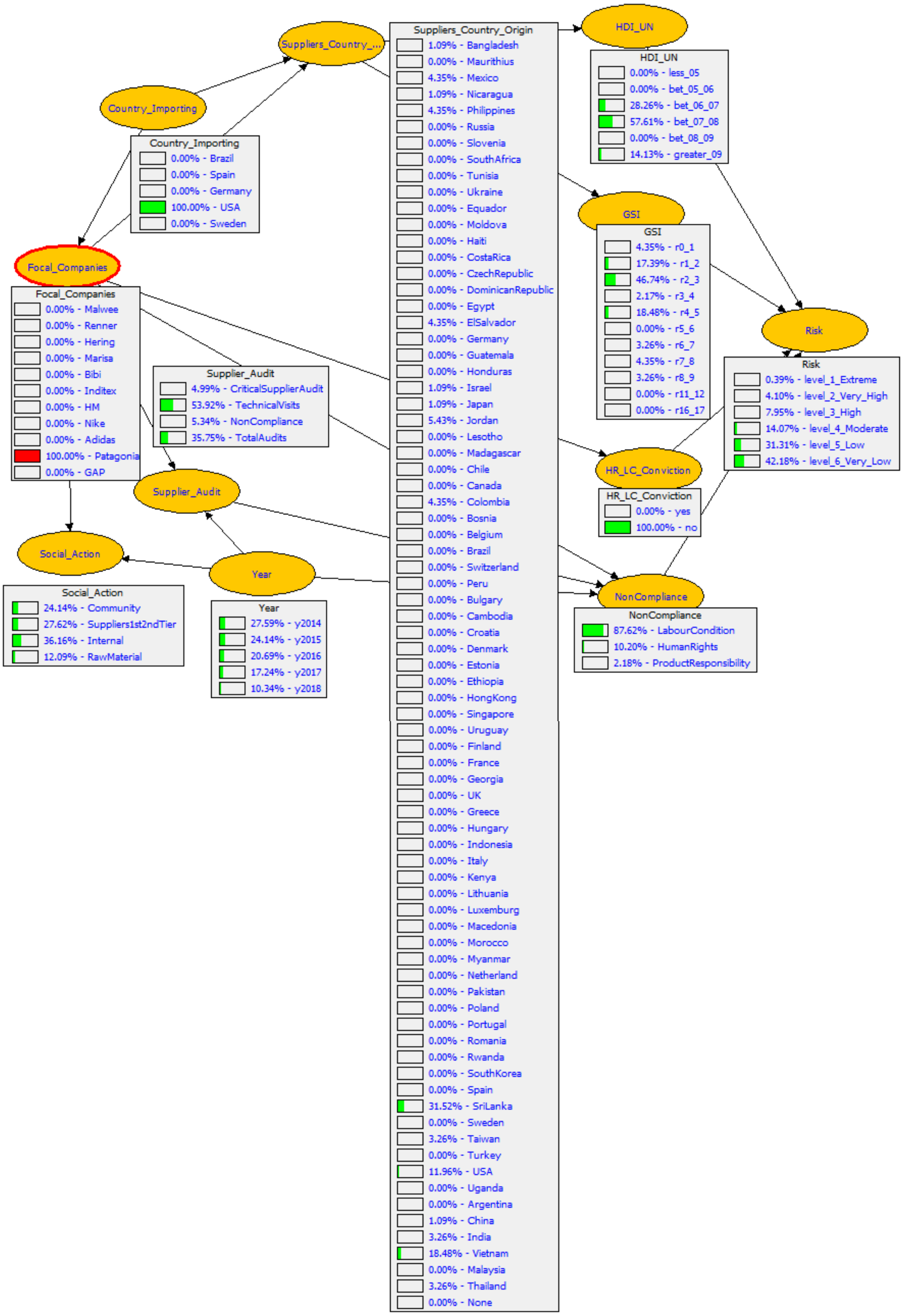
4.8 – Inference of risk probability level for company Nike



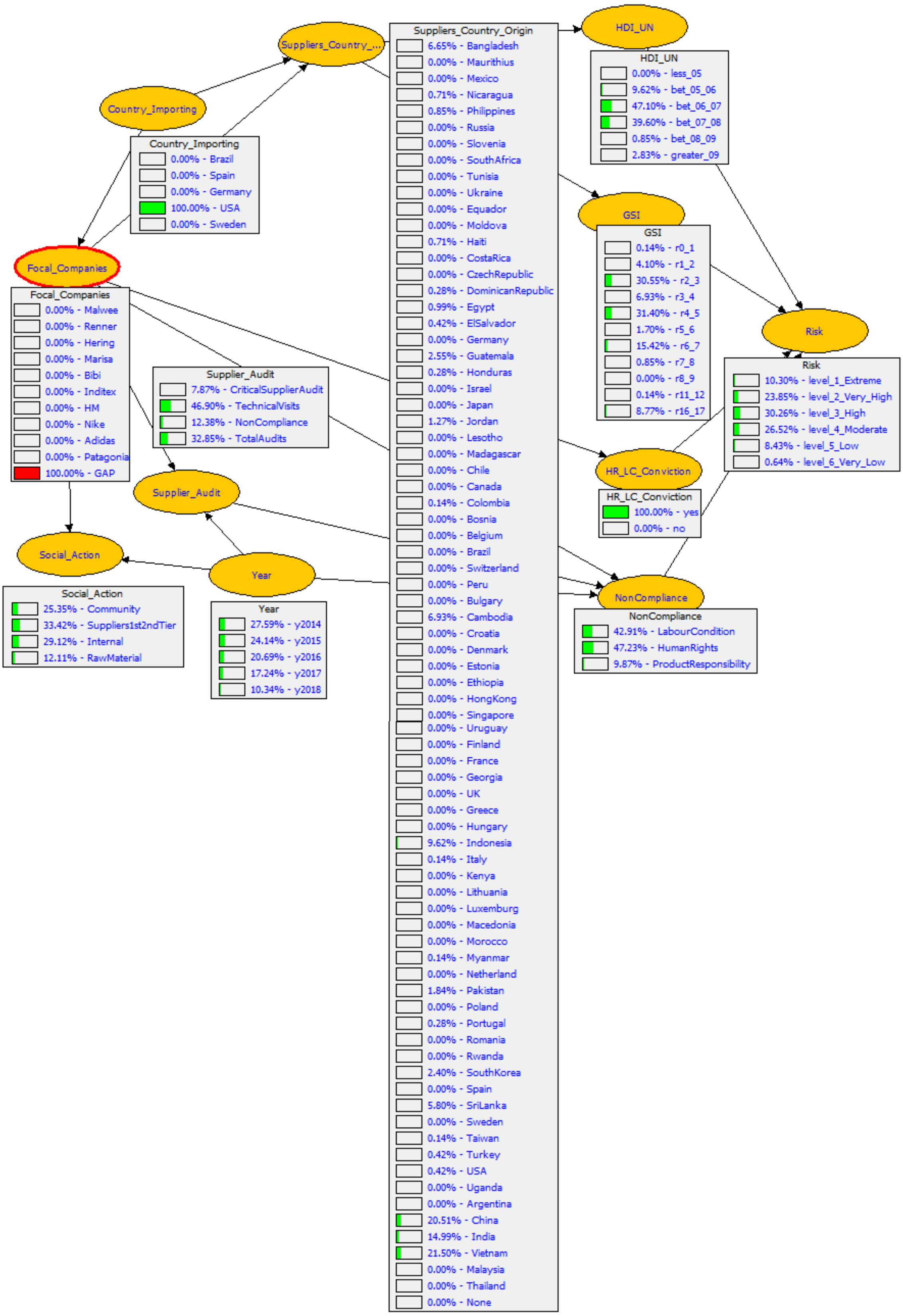
4.9 – Inference of risk probability level for company Adidas



4.10 – Inference of risk probability level for company Patagonia



4.11 – Inference of risk probability level for company GAP



Appendix 5 – Suppliers per country based on suppliers list information of all six companies analysed (number of suppliers, factories, workers and subcontractors)

Adidas
551 factories
706,000 workers
52 countries

	Tier 1	Sub contractor
Argentina	8	2
Bangladesh	4	0
Belgium	2	0
Bosnia and Hezergovi	0	1
Brazil	15	10
Cambodia	19	1
Canada	6	0
Chile	1	0
China	109	21
Colombia	1	0
Costa Rica	1	0
Czech Republic	1	0
Dominican Republic	1	0
Egypt	1	0
El Salvador	4	1
Georgia	1	0
Germany	11	0
Guatemala	1	2
Honduras	4	0
Hungary	2	0
India	22	10
Indonesia	43	5
Israel	1	0
Italy	11	0
Japan	30	0
Jordan	2	0
South Korea	36	33
Lesotho	1	0
Lithuania	1	0
Madagascar	1	0
Malaysia	3	0
Mauritius	2	0
Mexico	3	0
Myanmar	5	1
Nicaragua	2	0
Pakistan	16	1
Philippines	10	1
Poland	1	0
Portugal	4	1
Russia	1	0
Slovenia	1	1
South Africa	4	1
Spain	6	1
Sri Lanka	3	0
Taiwan	17	0
Thailand	10	3
Tunisia	2	1
Turkey	10	4
Ukraine	2	1
UK	10	0
USA	31	16
Vietnam	68	14

Nike
525 factories
1,052,195 workers
40 countries

	Tier 1	Sub contractor
ARGENTINA	12	2
Bosnia and Herzegovina	1	0
BRAZIL	23	4
BULGARIA	1	0
CAMBODIA	12	0
CANADA	3	0
China	121	13
CROATIA	1	0
ECUADOR	1	0
EGYPT	5	0
EL SALVADOR	4	2
GEORGIA	2	0
GERMANY	1	0
GREECE	1	0
GUATEMALA	6	0
HONDURAS	7	0
INDIA	8	1
INDONESIA	41	6
ISRAEL	1	1
ITALY	18	0
JAPAN	12	0
JORDAN	3	0
Korea (Republic of)	15	1
MALAYSIA	8	0
MEXICO	14	1
Moldova (Republic of)	4	0
NETHERLANDS	2	0
NICARAGUA	2	0
Pakistan	6	0
POLAND	1	0
ROMANIA	1	0
SOUTH AFRICA	1	0
SPAIN	1	0
SRI LANKA	17	0
Taiwan, Province of China	35	0
THAILAND	33	3
TURKEY	5	1
UK	1	0
USA	42	2
Viet Nam	122	15

Inditex
1449 factories
2 million workers
23 countries

	Tier 1	Sub contractor
ARGENTINA	37	
BANGLADESH	114	
BULGARIA	2	
BRAZIL	12	
CAMBODIA	5	
CHINA	393	
CZECH REPUBLIC	1	
EGYPT	3	
FRANCE	4	
GERMANY	1	
INDIA	131	
ITALY	44	
KOREA (SOUTH)	3	
LITHUANIA	1	
MOROCCO	121	
PAKISTAN	45	
POLAND	2	
PORTUGAL	161	
SPAIN	198	
SRI LANKA	1	
TUNISIA	3	
TURKEY	189	
VIETNAM	5	
	1476	

GAP
707 factories
1 million workers
25 countries

	Tier 1	Sub contractor	workers
BANGLADESH	47		125000
Cambodia	49		68000
China	145		284000
Colombia	1		800
Dominican Republic	2		1000
Egypt	7		8000
El Salvador	3		1800
Guatemala	18		12000
Haiti	5		14000
Honduras	2		2900
India	106		118000
Indonesia	68		78000
Italy	1		300
Jordan	9		6000
Myanmar	1		2800
Nicaragua	5		6500
Pakistan	13		22000
Philippines	6		2500
Portugal	2		500
South Korea	17		8000
Sri Lanka	41		39500
Taiwan	1		800
Turkey	3		500
USA	3		100
Vietnam	152		202000

H&M
655 factories
930,000 workers
41 countries

	Suppliers	Manufacturing	Suppliers	Production	Suppliers 3 tier	Workers
BANGLADESH	51	264	111	356	72	476735
Bulgaria	5	8	1	2	0	1970
Cambodia	22	31	13	21	0	95820
China	44	435	42	312	166	
Croatia	1	1	0	0	0	
Czech Republic	3	3	0	0	0	
Denmark	2	2	0	0	0	
Estonia	1	2	0	0	0	
Ethiopia	10	10	0	0	0	
Finland	4	4	0	0	0	
France	9	15	3	5	0	
Georgia	2	2	1	1	0	
Germany	7	11	0	0	0	
Great Britain	1	1	0	0	0	
Greece	2	2	0	0	0	
Hungary	3	3	0	0	0	
India	79	176	46	104	19	
Indonesia	37	68	20	54	8	
Italy	39	93	16	23	11	
Kenya	1	2	1	2	0	
Lithuania	3	3	0	0	0	
Luxembourg	1	1	0	0	0	
Macedonia Fyro	1	1	0	0	0	
Morocco	1	4	1	1	0	
Myanmar	30	43	17	28	3	
Netherlands	1	1	0	0	0	
Pakistan	15	30	10	13	8	
Poland	6	8	0	0	0	
Portugal	22	65	5	6	3	
Romania	7	25	6	8	0	
Rwanda	1	1	0	0	0	
South Korea	2	3	1	2	1	
Spain	3	3	0	0	0	
Sri Lanka	7	13	1	1	0	
Sweden	13	13	2	2	0	
Taiwan		0	0	0	3	
Thailand	2	2	0	0	0	
Turkey	63	214	42	164	46	
USA	4	4	0	0	0	
Uganda	1	1	0	0	0	
Vietnam	34	45	7	11	7	

Patagonia
102 factories
78,000 workers

	Tier 1	Sub contractor	Workers
BANGLADESH	1	0	5438
China	9	2	26230
Colombia	3	1	
El Salvador	3	1	1750
India	2	1	1704
Israel	1	0	0
Japan	1	0	3420
Jordan	3	2	0
Mexico	4	0	2757
Nicaragua	1	0	2160
Philippines	3	1	1002
Sri Lanka	19	10	9656
Taiwan	3	0	3993
Thailand	3	0	6924
USA	9	2	1762
Vietnam	16	1	42907