Proceedings of the 8th European Conference on Industrial Engineering and Operations Management
Paris, France, July 2-4, 2025

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/EU08.20250285
Published: July 2, 2025

Modelling and Sustainability Index Assessment of Biocomposites Supply Chain Networks Using Bayesian Belief Networks: A Case Study on Hemp-based Pellet Production

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Abstract

Planning sustainable supply chains (SCs) for emerging biocomposite materials is critical for balancing environmental, economic, and social dimensions in strategic decision-making, towards industrial success. In biocomposite SCs, early-stage pre-processing activities, such as biomass collection and particle size reduction, play a pivotal role in determining downstream sustainability outcomes. However, evaluating the performance of different SC scenarios under changing conditions remains difficult due to the non-linear interdependencies and uncertainty across SC components. This study presents a knowledge-driven Bayesian Belief Network (BBN) framework to support sustainability assessment of a complex hemp-based biocomposite SC case study under uncertainty. A novel metric, the Supply Chain Sustainability Index (SCSI), is introduced to quantify the overall probability of achieving the target sustainability performance level and assess the vulnerability of each underlying indicator. The BNN model integrates both expert insights and empirical relationships through regression-informed Conditional Probability Tables (CPTs) and causal graphs, across 15 proposed criteria of measurement spanning economic (e.g., Net Present Value (NPV), Conditional Value at Risk (CVaR), costs), technical (e.g., product quality, Technology Readiness Level (TRL)), social (e.g., job creation), and environmental (e.g., carcinogenic and ecotoxic impacts) factors. The scenario-based simulation and entropy-based sensitivity analyses are also conducted to identify the most influential factors among the criteria trade-offs. The results showed that the economic and technical factors, in the present case study, have the greatest influence on overall sustainability, while the social and environmental indicators revealed comparatively moderate effects.

Keywords
Bayesian Belief Network; Biocomposites, Sensitivity Analysis, Supply Chain Performance, SC Sustainability Index (SCSI).

1. Introduction

Biocomposites, particularly those derived from industrial hemp, have gained attention as renewable alternatives to petroleum-based materials, offering advantages such as biodegradability, low environmental impact, growing market demand, especially in Canada (García-García et al., 2015; Terzopoulou et al., 2015). Yet, the lack of fiber pre-processing infrastructure presents a significant barrier to scaling up production, emphasizing the need for informed strategic decision planning (Cherney & Small, 2016; Herrera-Franco & Valadez-González, 2004). Hemp-based biocomposites are used in sectors such as automotive, construction, and packaging, where there is increasing pressure to minimize carbon footprints and transition to circular economy practices. For such materials, sustainability assessments are essential not only for environmental accountability but also for guiding investment and enhancing competitiveness (Akbariansaravi, 2025).

Supply Chains (SCs) encompass interconnected processes from raw material sourcing to product production, and delivery. However, balancing economic viability, operational efficiency, environmental, and social responsibility across diverse functional units remain a key challenge, often resulting in systemic inefficiencies and risks. By nature, risk is unpredictable, and SC managers must be aware of both its likelihood and potential severity. A disruption in one part of the SC can trigger cascading effects across other segments, amplifying the impact and introducing additional layers of risk (Koh et al., 2017). Encountering risk at any point/indicator (unfavored level) can cause entire system of SC to reduce its performance (Mugoni et al., 2024). In this context, achieving resilient and sustainable SCs requires robust prediction methods to identify root causes, capture interdependencies, and manage uncertainty across interconnected dimensions, enabling the prediction of how unfavorable indicators may impact overall SC performance.

In the context of biocomposites, understanding how technical, economic, social, and environmental factors interact is crucial for designing sustainable and resilient SC configurations. Yet, decision-making in such SCs often occurs nearly in silos, engineering, procurement, and environmental departments operate independently, resulting in conflicting priorities and fragmented strategies (Flynn et al., 2010; PAGELL & WU, 2009). Procurement may focus solely on cost, while engineers target quality or reliability, with little visibility into broader sustainability implications. These fragmented decisions are particularly risky in emerging industries like biocomposites, where uncertainty is high and interdependencies are non-trivial.

Scenario-based analysis and sensitivity testing provide a systematic means to anticipate the performance of SCs under changing stats of sustainability indicators, allowing stakeholders to evaluate future trade-offs and risks. These methods have been shown to improve planning confidence, particularly when integrated with probabilistic modeling techniques (Büyüközkan et al., 2015; Peng Wong & Yew Wong, 2007). Bayesian Belief Networks (BBNs) are known as powerful tools for managerial assessments and decision support under uncertainty. BBNs are probabilistic graphical models that integrate expert insights, often gathered through interviews, with data-driven causal relationships among system variables, represented through nodes and directed arcs (Rabbi et al., 2020b). They allow for real-time updating of beliefs using Bayes' theorem, enabling both diagnostic and predictive reasoning. When combined with scenario-based simulation and entropy-driven sensitivity analysis, BBNs provide an interpretable framework for evaluating the systemic impact of sustainability indicators, even in data-scarce contexts of biocomposite manufacturing SC. Despite their potential, few studies have integrated all four sustainability pillars, technical, economic, environmental, and social, into a unified BBN model tailored for biocomposite SCs. For example, prior researchers, such as Odu (2019), have primarily focused on sectors like oil and gas or aviation risk (Ojha et al., 2018), leaving a notable gap in the application of BBNs within sustainability-focused SC models for emerging materials like biocomposites.

1.1 Objective

This study aims to develop a scenario-based analytical framework to evaluate the impact of sustainability performance indicators on risk management within biocomposite SCs. To this end, a probabilistic, graph-based decision-support system is employed using the BBN methodology. The specific sub-objectives of the work, through a selected industrial case study, are to:

1) **Model the combined performance of sustainability factors**, including technical, economic, environmental, and social dimensions, by capturing causal relationships and uncertainty propagation.
2) **Estimate the likelihood of various performance outcomes and their impact on SC bahavior,** incorporating expert-driven knowledge, suited for data-scarce contexts like biocomposites.

3) **Develop a Supply Chain Sustainability Index (SCSI)** to identify vulnerable nodes within the biocomposites SC network, supporting real-time, scenario-based decision-making through an interpretable framework that supports cross-functional coordination.

2. Background Review

Sustainability performance in SCs increasingly demands the integration of multiple, interdependent criteria, namely economic, environmental, social, and technical factors. Prior studies have consistently shown that sustainable SC configurations yield long-term benefits such as reduced costs, enhanced quality, minimized waste, and improved operational performance (Olhager and Prajogo, 2012). However, evaluating trade-offs among these factors remains challenging, particularly when performance indicators are interdependent and data availability is limited (Peng Wong and Yew Wong, 2007).

To manage such complexity, probabilistic scenario-based analysis has emerged as a powerful risk management tool for exploring future outcomes under uncertain or evolving conditions. It enables decision-makers to assess system performance under different configurations and risk profiles before actual implementation (Peng Wong and Yew Wong, 2007). Several earlier studies, such as Tuncel and Alpan (2010) and Giannakis and Papadopoulos (2016), addressed sustainability risk management in SCs through scenario analysis and causal diagrams, however, they largely rely on deterministic assessments including Multi-Criteria Decision-Making (MCDM) approaches, such as AHP, Analytic Network Process (ANP), or Delphi-based methods. Also, while numerous studies have addressed risk management within SCs, most have focused specifically on supplier selection (Levary, 2007). These deterministic approaches map risks and outcomes without incorporating probabilistic reasoning, limiting their ability to capture uncertainty propagation or provide dynamic insights under evolving conditions (Alfaro-Saiz et al., 2020; Li and Mathiyazhagan, 2018).

More recent research has emphasized the need for interactive, probabilistic frameworks that can account for cascading impacts and interdependencies among sustainability factors, especially under data-scarce or high-uncertainty environments (Rabbi et al., 2020b). To support such analysis, BBNs have gained increasing traction. For instance, Chiu and Choi (2016) reviewed various mean-variance and probabilistic methods for SC risk modeling, advocating for BBNs in situations of uncertain or incomplete information. Similarly, Enyoghas and Badurdeen (2023) applied a BBN-based approach to assess risk likelihood in sustainable product design, highlighting the importance of capturing causal relationships to guide design decisions. Also, Rabbi et al. (2020a) developed a BBN model to predict green SC performance by linking key performance indicators with sustainability objectives. Dohale et al. (2021) integrated MCDM, Delphi, and Bayesian modeling for production system selection. Qazi et al. (2023) employed a network-based risk model using Conditional Value-at-Risk (CVaR) to evaluate sustainability risk under uncertain customer behavior.

These aforementioned studies collectively emphasize the usefulness of BBNs in structuring expert knowledge, quantifying uncertainty, and determining the relationship among various enablers of SC risk assessment. However, many of these applications relied on manually constructed Conditional Probability Tables (CPTs), often derived from expert scoring or simplified assumptions. For example, Büyüközkan et al. (2015) and Dong et al. (2010) generated CPTs based on expert-derived dependency matrices, which may lack transparency, reproducibility, and responsiveness to data evolution, especially in emerging sectors like biocomposites.

The present work addresses that gap by developing a **novel integration of regression-based CPTs in sustainability modeling under BBN**, where high-level sustainability metrics are informed by empirically estimated parent-child (cause-effect) relationships. This hybrid modeling strategy enhances the quantification of CPT, enabling dynamic learning while preserving logical coherence. The **theoretical contributions of this framework** include: (1) bridging subjective expert insights and empirical data through conditional logic and regression-informed CPTs, (2) visually interpretable tool to support risk-informed multi-criteria sustainability evaluation, specifically adapted to biocomposite manufacturing scenarios where lifecycle complexity and uncertainty are high. This hybrid strategy integrates expert judgment with regression-based logic to preserve causal integrity while reducing subjectivity. It also supports dynamic learning by allowing updates as new data becomes available. By focusing on hemp-based biocomposites as a case study, the model not only supports sustainable performance forecasting but also guides SC managers for risk-aware strategic decisions in processing infrastructure, product development, and policy alignment.

3. Case Study and Methodology

To demonstrate the applicability of the BBN framework in a real-world industrial setting, a case study was conducted on the SC of hemp-based biocomposite production as shown in Figure 1, focusing on grinding equipment selection.

The SC includes four key stages, each interconnected through the flow of materials: harvesting, transportation, pre-processing, and biocomposite production. Strategic decisions at each stage, such as selecting the fiber size reduction equipment during hemp pre-processing, affect interconnected factors like product quality, recurring cost, environmental impact, and job quantities. For example, half-screen grinding improves technical performance by producing finer particles ideal as biofillers in reinforcing biocomposite, but it may also raise recurring costs and emissions due to higher energy requirement (Akbarian-Saravi et al., 2024). The BBN framework captures these trade-offs and causal relationships, managing uncertainty.

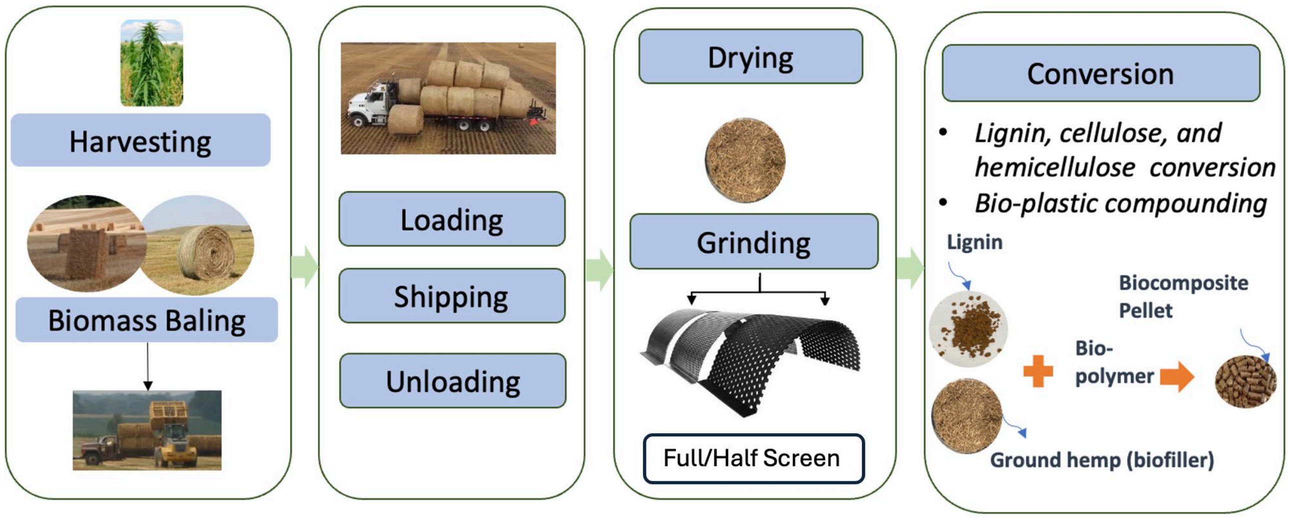


Figure 1. Process flow of hemp-based biocomposite production used in the BBN case study.

Figure 2 illustrates the overall methodological framework adopted in this study for risk assessment of sustainable biocomposites SC design performance located in Saskatchewan, Canada, using a BBN. The process begins by identifying input variables across the four foundational pillars of sustainability, economic, environmental, social, and technical, which collectively guide decision-making in sustainable SC assessment. Economic and environmental performance indicators are derived from the earlier studies performed by Akbarian-Saravi et al. (2025a, 2025b, 2025c) using Techno-Economic Analysis (TEA) and Life Cycle Assessment (LCA) modeling within the same case study, while social and technical indicators relied on industry expert interviews and literature. These include indicators such as recurring and non-recurring costs, Net Present Value (NPV), environmental impacts (e.g., carcinogenic and non-carcinogenic effects), job quantities, product quality, system reliability, and Technology Readiness Level (TRL). These factors interact within the BBN structure to quantify their probabilistic dependencies, ultimately contributing to the Supply Chain Sustainability Index (SCSI), a composite indicator representing the integrated sustainability performance of the entire SC.

As shown in Figure 2, the BBN modeling process starts with constructing a causal diagram to capture variable interdependencies and identify potential case-and-effect pathways among sustainability indicators. This step includes developing a case-and effect matrix among selected criteria to map upstream and downstream relationships. Next, a Bayesian map is formulated by translating these relationships into nodes and edges within a directed acyclic graph (DAG), representing conditional dependencies across indicators. Next, to parameterize the network, a dependency matrix is constructed using a regression-informed approach, which integrates expert knowledge with observed data to generate Conditional Probability Tables (CPTs).

The model was implemented in Norsys Netica, where Bayes' theorem is used to update posterior probabilities based on new evidence (Langseth and Portinale, 2007; Mahadevan et al., 2001). Using Bayes' theorem, the model continuously updates probabilities based on new evidence. For defining Joint Probability Distribution (JPD), objective or subjective probabilities can be incorporated in the CPT in which for conditional probabilities, Bayes' theorem for the *n* mutually exclusive hypothesis $(i = 1, .., n)$ is used as described in Equation (1), which is derived employing the joint probability definition given in Equation (2), then arranged as Equation (3). Following model construction, scenario-based simulations are conducted to evaluate how changes in the state of key input indicators affect overall SC sustainability performance. These simulations offer a dynamic framework to explore trade-offs and assess the resilience of SC configurations under uncertainty and risk. To complement this, sensitivity analysis using the entropy reduction method is applied to identify the most influential variables, thereby informing decision-makers on where targeted interventions can yield the greatest sustainability gains.

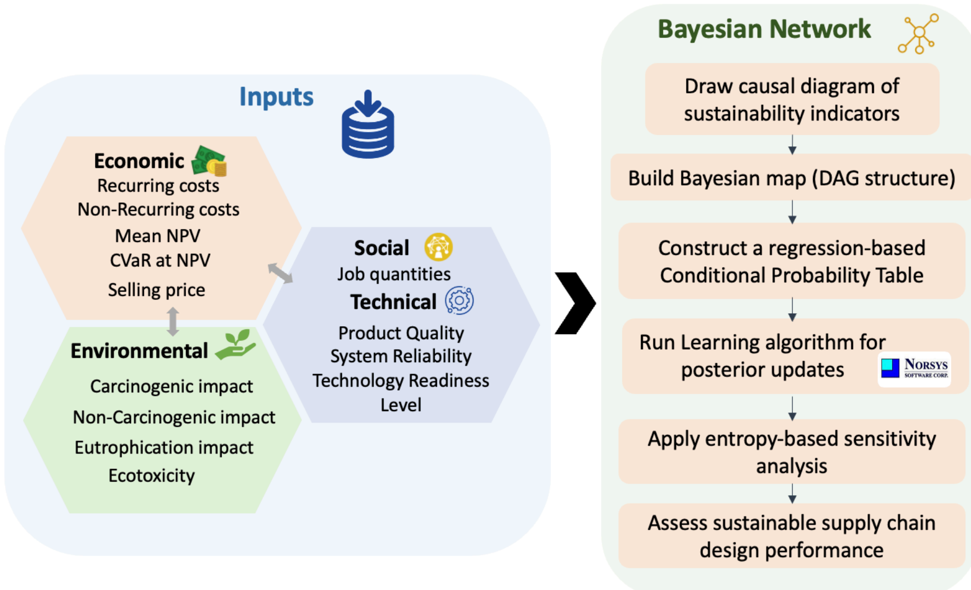


Figure 2. Methodological framework to establish the BBN model in the case study.

$$P(H_j|E) = \frac{p(E|H_j) \times p(H_j)}{\sum_{i=1}^{n} p(E|H_j) \times p(H_j)} \tag{1}$$

$$P(H \cap E) = p(E|H) \times p(H) = p(H|E) \times p(E) \tag{2}$$

$$p(H|E) = \frac{p(E|H) \times p(H)}{p(E)} \tag{3}$$

Where $P(H_j|E)$ is the posterior probability for the hypothesis (H_j) updating from evidence (E) defined as inference in BBN. $p(H_j)$ and $p(E|H_j)$ indicate the prior probability and the conditional probability, respectively. For instance, a formula of Bayes' theorem for two competing hypotheses is given in Equation (4).

$$p(A|B) = \frac{p(B|A) \times p(A)}{p(B|A) \times p(A) + p(B|A') \times p(A')} \tag{4}$$

3.1 Generation of Unconditional Probability

The prior and posterior probabilities are determined after building a causal diagram. Prior probabilities are derived from expert knowledge and literature. This qualitative input (as per Table 1) is then converted into a quantitative format suitable for the CPTs in the BBN model using Equation (5). To do this, the condition states are ranked by importance, and reciprocal values of these ranks are used to assign prior probabilities per prior work by Crawford et al. (2020). For example, when the mean NPV states are ranked with "High" assigned a score of 1 and "Low" a score of 2, the corresponding prior probabilities are computed as 66.7% for High and 33.3% for Low.

$$w_j = \frac{\frac{1}{r_j}}{\sum_{k=1}^{n} \frac{1}{r_k}} \tag{5}$$

Where n is the number of attributes. The rank of the j^{th} state is r_j, and the score of the k^{th} attribute is r_k.

3.2 Conditional Probability Estimation Using Classification and Regression-Based Logic

After establishing the prior probability, the posterior probability is then determined. The CPT in the BBN were constructed using a hybrid approach that combines qualitative classification with regression-informed simulation, reflecting the complex realities of SC to help in assessing the risk exposure associated with key SC performance indicators (C.-H. Chiu and Choi, 2016).

3.2.1 Qualitative Classification of Influencing Variables

The study used expert elicitation combined with categorized input values (e.g., 1-5 Likert Scales) to define states of influencing variables and derive CPTs for Bayesian networks (Alkhairy et al., 2020). These thresholds were applied consistently across all relevant variables, including product quality, TRL, environmental impact, and job quantity. As shown in Table 1, for most indicators, a "High" state reflects the preferred condition. However, for environmental performance, the "Low" state (e.g., lower emissions) is considered more desirable, aligning with sustainability goals.

Table 1. Classification of sustainability-related performance indicators using Likert-scale thresholds.

Performance Indicators			5-point Likert scale assignment	
			1-3 (preferred)	**4-5 (less preferred)**
1	Sub-Indicators	Mean NPV	High	Low
2		Recurring Costs	Low	High
3		Non-Recurring Cost	Low	High
4		Selling Price	High	Low
5		CVaR at NPV	High	Low
6		Technology Readiness level	High	Low
7		Product Quality	High	Low
8		System Reliability	High	Low
9		Job Quantities	High	Low
10	Main Indicators	Economic (profits)	High	Low
11		Environmental (emissions)	Low	High
12		Social	High	Low
13	BNN Final Output Node	SC Sustainability Index	High	Low

3.2.2 Simulated Population of Dependent Variables

To map the interdependencies among variables, an interaction matrix was developed as shown in Figure 3. The matrix highlights direct dependencies between parent and child nodes used in the BBN. Each cell denotes whether a variable (row) is influenced by another variable (column), with a value of 1 indicating a dependency. For example, recurring and non-recurring costs typically scale with process TRL. This binary structure facilitates transparency in modeling causal relationships and supports the construction of CPTs based on expert input. Each qualitative state (e.g., Low or High) was mapped to a representative numerical value, to streamline building of CPTs, using the midpoint of its respective interval, 2 for the preferred range (1–3) and 4.5 for the less-preferred range (4–5), as defined in Table 1. These values were used to simulate realistic interactions between parent and child nodes. Once a target state for a dependent node (e.g., Recurring Cost = 2) was defined, state of input variables (e.g., product quality, TRL, job quantities) were conditionally sampled from their appropriate ranges using logic-based random functions (e.g.,

=IF([Node]=2, RANDBETWEEN(1,3), RANDBETWEEN(4,5))). This simulation-based approach enables efficient CPT population while maintaining logical consistency, particularly in data-scarce environments (Maleki et al., 2013).

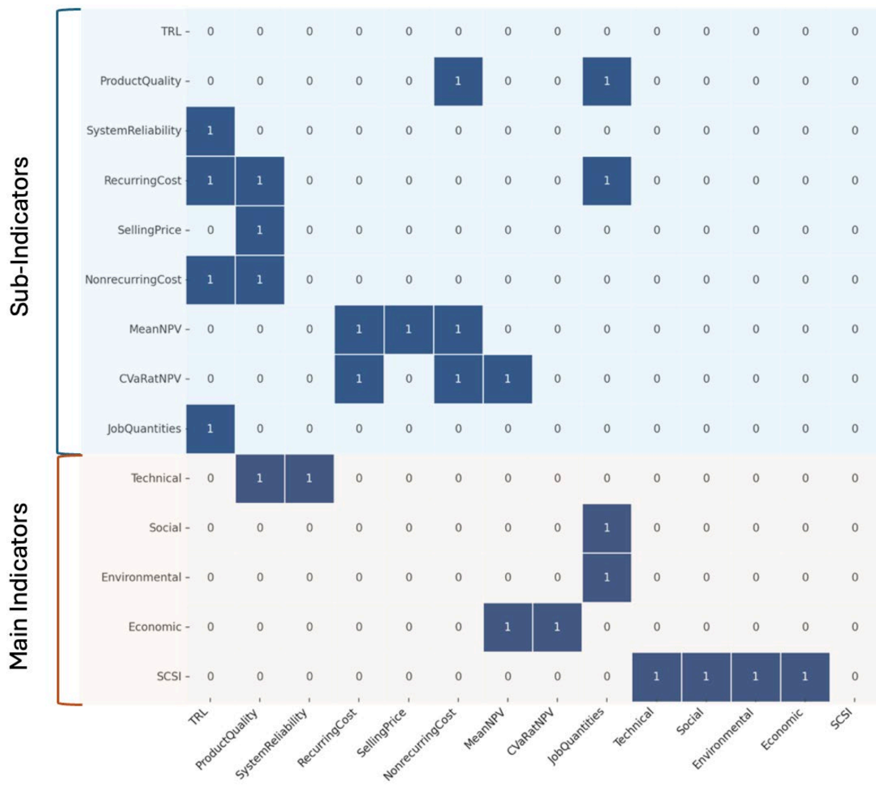


Figure 3. Dependency matrix for Bayesian Belief Network (BBN) nodes in the present sustainable SC assessment. Columns represent parent nodes contributing to the Conditional Probability Tables (CPTs) of the corresponding row nodes. Highlighted cells indicate causal relationships derived from expert input and scenario-based logic.

3.2.3 Regression-Based Support for Conditional Structure

To enhance the robustness and traceability of the CPT design, multiple linear regression analysis was used to confirm and quantify the influence of parent variables on the dependent node. The general regression model used is explained in Eq. (6):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{6}$$

Where Y is depended on variable (e.g., recurring cost, or the SCSI, etc.), X_i is independent variables (e.g., product quality, TRL, job quantity, etc.), and β_i is Coefficients representing the strength of influence. The methodological foundation of this study aligns conceptually with the Bayesian regression-based CPT quantification framework introduced by Alkhairy et al. (2020), wherein expert-elicited scenario assessments are encoded through logistic regression to construct probabilistic relationships. Although our approach does not implement a formal logistic or Generalized Linear Model (GLM), it adopts a structured, simulation-based logic to conditionally populate parent node states based on predefined outcomes of dependent variables. Instead of fitting statistical models, qualitative states (e.g., "low" or "High") are mapped to value ranges and populated using constrained random sampling guided by expert input. This approach maintains logical consistency across the Bayesian network and supports the encoding of domain knowledge under uncertainty. As such, the framework represents a practical extension of regression-informed CPT construction, designed for settings where empirical data are limited but expert judgment is critical for defining conditional dependencies.

For instance, to parameterize the SCSI node within the BBN, the results from a multiple linear regression model were employed as functional inputs. After implementing linear regression on the generated CPT population per section 3.2.2, the regression coefficients (Table 2) quantify the influence of key sustainability dimensions, Economic, Environmental, Social, and Technical, on the SCSI. A positive coefficient for the main indicators suggests that improvements in economic (e.g., profit), social, and technical performance contribute to a higher sustainability score. Conversely, a negative coefficient for environmental emissions indicates that lower emission levels are necessary to enhance sustainability. Furthermore, *p-values* below 0.05 demonstrate that the corresponding variables have a statistically significant relationship with the dependent variable, the SCSI, at a 95% confidence level.

Table 2. Multiple regression results for estimating the Supply Chain Sustainability Index (SCSI). All predictors are statistically significant ($p < 0.01$), and the model explains 95% of the variance in SCSI (Adjusted $R^2 = 0.946$).

Predictor	**Coefficients**	**Standard Error**	**T Stat**	**P-value**	**Lower 95%**	**Upper 95%**	**Lower 95.0%**	**Upper 95.0%**
Intercept	1.079	0.410	2.628	0.011	0.251	1.907	0.251	1.907
Economic	0.194	0.073	2.632	0.016	0.045	0.342	0.045	0.342
Environmental	-0.185	0.060	-3.079	0.003	-0.307	-0.064	-0.307	-0.064
Social	0.251	0.074	3.391	0.001	0.102	0.401	0.102	0.401
Technical	0.377	0.071	5.269	0.000003	0.232	0.521	0.232	0.521

4. Results and Discussion

In this section, the constructed BBN model is analyzed to evaluate the risk management of SC associated with biocomposites. This section discusses how different variables, such as TRL, product quality, and cost factors, etc. interact and influence the four main sustainability dimensions: economic, environmental, social, and technical. This section presents the process of belief propagation through the dependency and directed graphical model and applies sensitivity analysis using entropy reduction to identify which input variables have the strongest influence on the SC Sustainability Index (SCSI). The goal is to determine the most influential drivers of sustainability performance in the SC configuration.

4.1 Baseline Probabilistic Inference

Based on Figure 4, under prior conditions, without any external evidence or interventions, the BBN assigns an 85.3% probability to the “High” state of the SCSI. The prior probability of each event is determined by the measured value of the corresponding indicator, with these values assigned based on expert judgment from industry professionals.

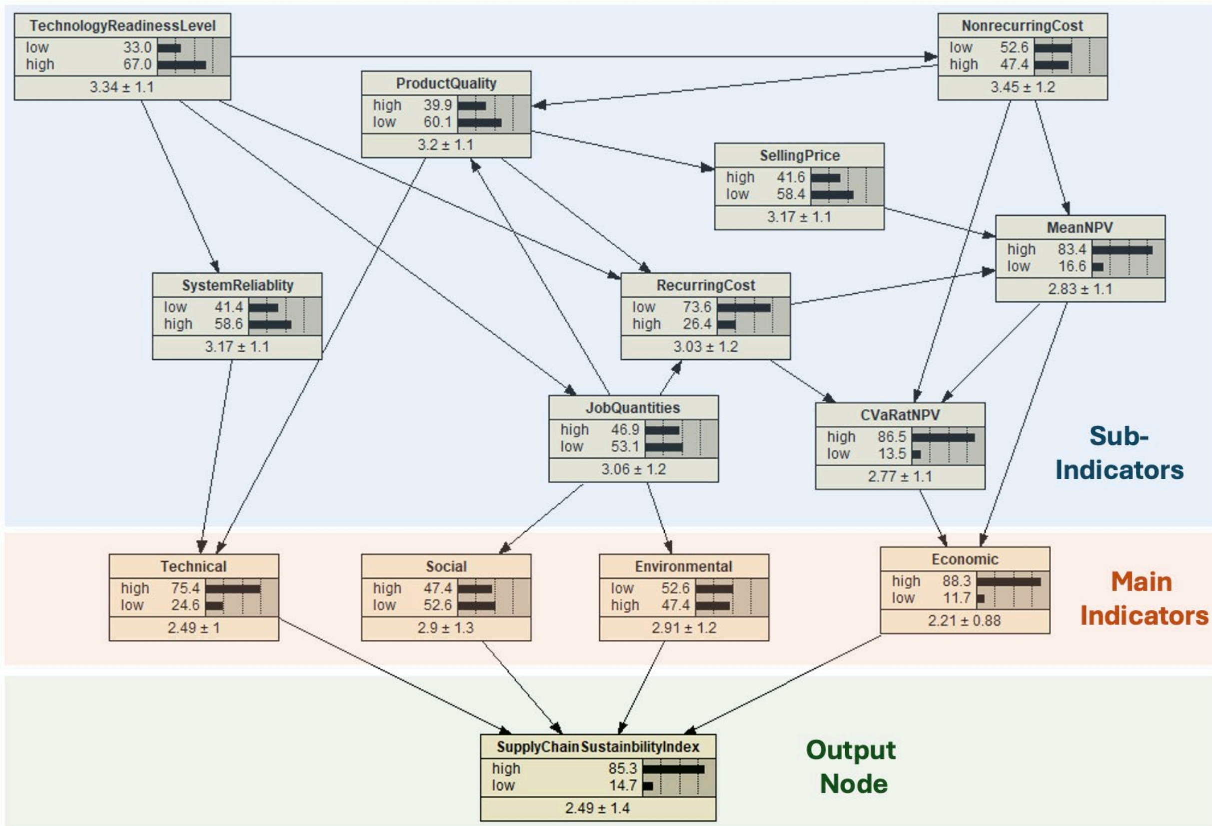


Figure 4. BBN model of hemp-based biocomposite supply chain sustainability.

The SCSI is used to identify the nodes that needs special attention from the managers. Based on the embedded probabilistic relationships, the system is likely to meet overall sustainability goals under average operating conditions. The technical and economic dimensions show the strongest performance with 75.4% and 88.3% probabilities in the "High" state, respectively. This indicates that the system is technologically mature and economically viable. These outcomes are driven by upstream contributors such as TRL (67% High), system reliability (58.6%), and strong financial indicators including CVaR at NPV (86.5% High), and mean NPV (83.4% High), balanced by moderate levels of recurring and non-recurring costs. The environmental dimension reflects moderate sustainability, with 52.6% of cases falling into the "Low" state. Conversely, the social dimension demonstrates the weakest performance, with just 47.4% in the "High" state, primarily influenced by job quantities, which remain moderately distributed. This implies that under current assumptions, social impacts, such as employment outcomes, are less certain and may require further intervention to strengthen sustainability performance during SC design decisions.

4.2 Scenario Modeling I: Backward SC Sustainability Performance

To explore the structural conditions supporting sustainability, the SCSI node was fixed to the "High" state with 100% certainty as shown in Figure 5. This inverse modeling approaches allow us to infer how other factors shift probabilistically to support such an outcome. The most significant shift was observed in the technical dimension, which increased its "High" probability from 75.4% to 78.3%, emphasizing the model's reliance on technological maturity and system reliability as key enablers of sustainability. Similarly, the economic dimension rose to 90.6%, reinforcing profitability as a critical, though secondary, contributor. The Environmental node also showed improvement, with the "Low" state (preferred) increasing to 53.5%, indicating a favorable ecological footprint under sustainable configurations. The social dimension increased modestly to 48.9%, suggesting that job creation is partially aligned with broader sustainability targets. In other scenario as shown in Figure 6, when the SCSI is set to the "Low" state with 100% certainty, backward inference reveals systemic deterioration across key dimensions. The probability of "High" performance drops across following factors: technical decreases from 88.3% to 58.2%, economic from 90.6% to 75.5%, and social from 47.4% to 38.4%, while Environmental sees a shift toward higher emissions with its "Low" (preferred) state falling from 52.6% to 47.3%.

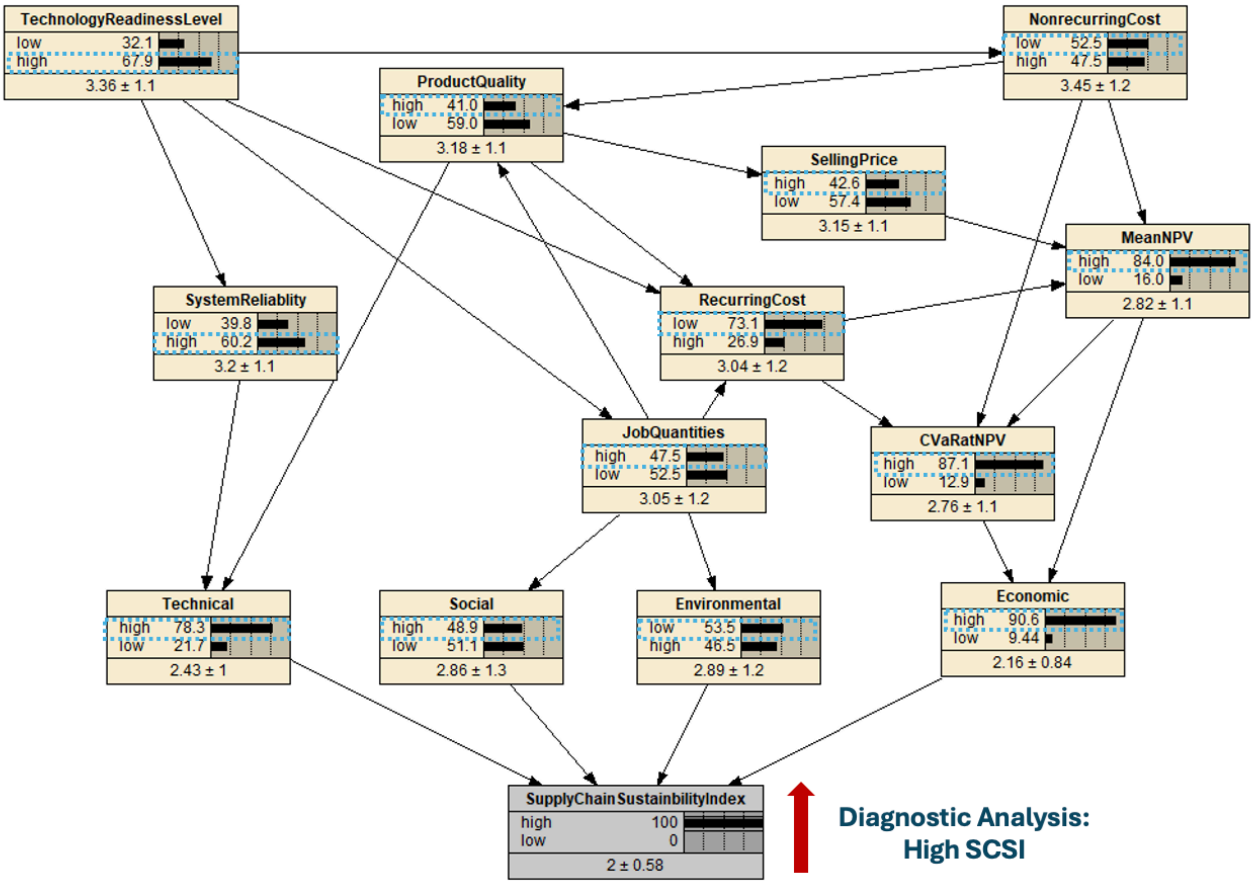


Figure 5. Backward inference scenario in the Bayesian Belief Network model, where the Supply Chain Sustainability Index (SCSI) is fixed to the "High" state (100%).

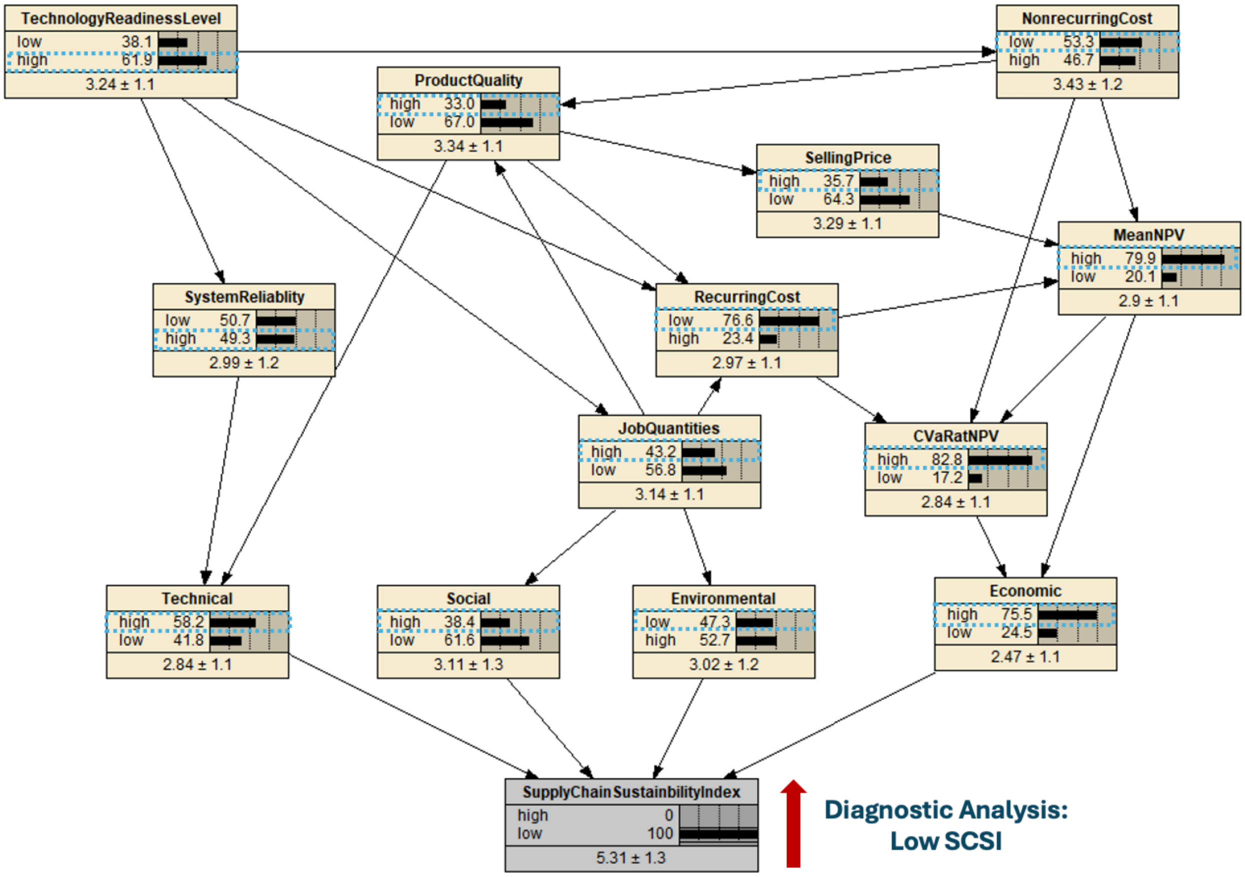


Figure 6. Backward inference scenario in the Bayesian Belief Network model when the SCSI is fixed at "Low" state (100%).

4.3 Scenario Modeling II: Forward Propagation from Technology Readiness Level

As a validation method, extreme-case scenario modeling, where TRL is fixed at its highest or lowest state, tests the BBN's robustness and ensures its predictions align with expert knowledge and expected system behavior. The results in Figure 7 reveal that TRL has the strongest influence on nodes directly tied to technological maturity. Notably, system reliability, job quantities, and non-recurring cost demonstrate the largest sensitivity to TRL shifts, with system reliability increasing by nearly 25% under high TRL and decreasing by over 50% under low TRL. This highlights TRL's critical role in ensuring system maturity and reliability. Conversely, Economic and SCSI show minimal variation, suggesting these outcomes are less directly influenced by TRL changes. Overall, the chart validates the model's logic by revealing that more mature technologies (high TRL) support stronger performance in key operational factors, while lower TRL introduces substantial systemic risks.

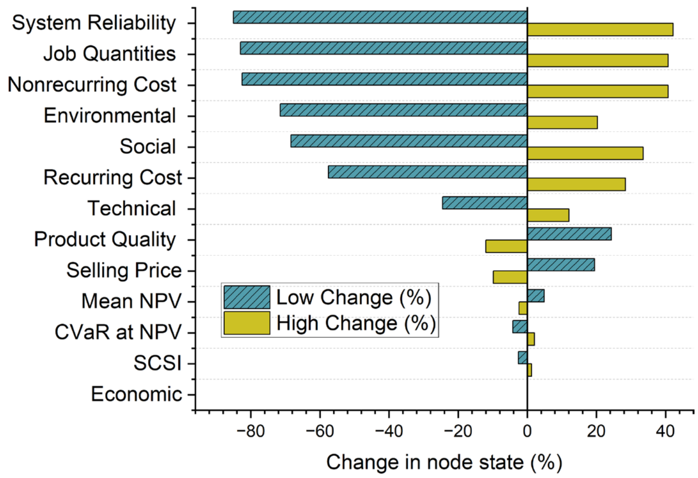
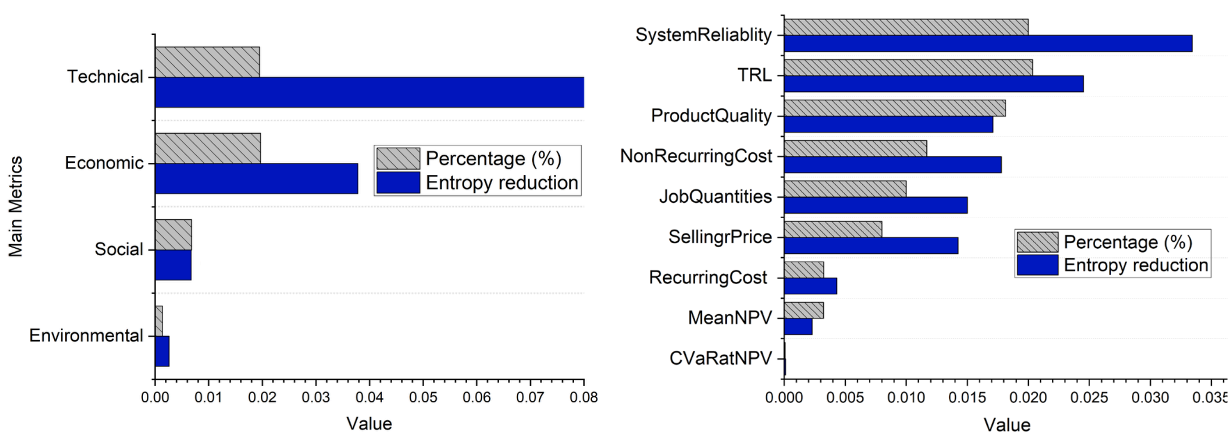


Figure 7. The impact of Technology Readiness Level (TRL) on the probability of key nodes.

4.4 Sensitivity Analysis

A sensitivity analysis was used to find crucial parameters affecting the sustainable SC performance and to quantitatively verify the model. The entropy reduction approach was used to calculate the reduction in mutual information (e.g., SCSI) from a new finding of a varying variable node (e.g., product quality) This analysis was conducted using Netica's built-in "Sensitivity to Findings" tool. Specifically, the tool computes metrics such as mutual information and entropy reduction, indicating how much each variable affects the uncertainty associated with the sustainability outcome. The SCSI node was selected as the target, and the analysis was performed under both unconditional and conditional scenarios. The analysis was divided into two layers: (1) direct sustainability pillars (technical, economic, environmental, social), and (2) upstream process drivers, including system-level and economic indicators. As shown in Figure 8 (a), among the four main sustainability pillars, the technical dimension shows the highest impact (*Entropy Reduction = 0.0737*), followed by *economic (0.0143).* These findings indicate that improved technical performance and profitability are central to achieving sustainable SC outcomes. In contrast, *social (0.0084)* and *environmental (0.0060)* dimensions demonstrate lower sensitivity. While still relevant, their influence on SCSI is comparatively weaker, suggesting that sustainability goals related to emissions including ecosystem and health-related impacts may require dedicated regulation or design mechanisms beyond core system. Similarly, in Figure 8 (b), at the sub-factor level, *system reliability (0.0325)*, *TRL* (*0.0285)*, and *product quality (0.0204)* emerge as the top contributors to sustainability performance. *Non-recurring cost (0.0148)* also demonstrates meaningful influence, reflecting the importance of managing capital-intensive decisions. On the other hand, nodes like *selling price (0.0046*), *job quantities (0.0042)*, and *CVaR at NPV (0.0028)* show limited impact in shaping overall sustainability outcomes. This suggests that while they play supportive roles, they are less critical when prioritizing systemic improvements.



(a) **(b)**

Figure 8. Sensitivity analysis of the Supply Chain Sustainability Index (SCSI) node, indicating the most crucial factors towards securing a high SCSI. (a) main metrics; (b) sub-indicators.

5. Conclusion

This study developed a probabilistic decision-support framework using a BBN, enhanced with regression-informed CPT logic, to automate CPT generation and evaluate sustainability in biocomposite SCs under uncertainty. Applied to a hemp-based pellet production case, the model captured the interdependencies across technical, environmental, economic, and social dimensions. The proposed SCSI served as a composite metric, revealing that Technical (88.3%) and Economic (75.4%) factors were the strongest contributors to overall sustainability and aggregated SC risk, while social and environmental factors had lower influence. Scenario modeling highlighted the role of high TRL, improved product quality, and manageable investment costs in driving sustainable outcomes. Sensitivity analysis identified system reliability (0.0325) and TRL (0.0285) as the most influential upstream variables, whereas CVaR at NPV (0.0028) and job quantities (0.0042) showed minimal effect. Overall, the model addressed the need for integrated, risk-aware tools to support cross-functional decision-making in biocomposite SC planning.

Beyond the SC modeling contribution, this framework offers direct value to policymakers and sustainability managers by translating complex trade-offs into interpretable, probabilistic outcomes to focus on areas that are more vulnerable to risk in decision-making. For instance, the model can inform infrastructure investment decisions, such as funding or incentives for high-reliability equipment in biocomposite facilities. Moreover, the SCSI provides a quantifiable benchmark to guide procurement criteria and carbon labeling policies. By integrating risk-aware modeling with scenario-based simulation, this framework enables evidence-based policy development in emerging biocomposite markets. It empowers decision-makers to define target sustainability performance levels and trace back the required conditions for each contributing indicator. Through diagnostic analysis, the model facilitates performance benchmarking and guides targeted interventions to align strategic decisions with overarching sustainability goals. Future work may explore two key directions. First, the proposed regression-informed Bayesian framework can be benchmarked against alternative weighting methods, such as fuzzy MCDM and entropy-based models, to evaluate differences in transparency, scalability, and automation in sustainability-driven decision-making. Second, the methodology can be validated through application to SCs in other industrial sectors, possibly with a refocus on also translating customer needs and expectations into the SC design (Kasaei et al., 2014). This would allow for broader comparison of effectiveness and generalizability, especially when combined with advanced belief propagation techniques to support automated scenario analysis under uncertainty.

Acknowledgement

This work was supported by the MITACS Accelerate Program (grant no. IT29287) and Advanced Biocarbon 3D Inc. Additionally, stipulating discussions with colleagues at the Composites Research Network (CRN).

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