# **An Integrated MCDM-ML Approach for Predicting the Carbon Neutrality Index in Manufacturing Supply Chains**

#### **Abstract**

Organisations across the globe are devising novel approaches to strive for carbon neutrality. Global institutions have manifested the critical need to develop reasonable strategies in every sector to mitigate the impending issues of excessive anthropogenic carbon emission and, in consequence, climate change. World-leading economies have initiated significant steps by developing zero-carbon emission policies to monitor the escalating carbon emissions to curb global warming. The clothing industry features a substantial carbon footprint while causing environmental pollution. Based on transition management theory, this study aims to explore and evaluate the critical determinants that can assist in pursuing carbon neutrality in the clothing industry. A decision support system comprising an integrated voting analytical hierarchy process (VAHP) and Bayesian network (BN) method to fulfil our purpose. Initially, pertinent literature is reviewed to determine the critical determinants for carbon neutrality (CDs-CN). After that, the VAHP method is employed to prioritise the CDs-CN. Further, the influence of CDs-CN on achieving carbon neutrality is modelled using a BN, predicting the carbon neutrality index (CNI) for the clothing industry. The findings reveal that professional expertise, laws and certifications, technological acceptance, availability of decarbonising methods, and adequate carbon offsetting are the essential CDs-CN. This research extends the existing knowledge on integrating MCDM-ML techniques to address predictive modellingbased problems involving complex structures. Simultaneously, the present study helps practitioners and policymakers understand the key CDs-CN to successfully build and manage a carbon-neutral clothing industry by adopting the suggested strategies. Finally, recommendations concerning sustainable development goals (SDGs) are provided to achieve carbon-neutral manufacturing supply chains.

#### **1 Introduction**

One of humanity's most pressing challenges is ever-happening climate change, as stipulated by the United Nations Sustainable Development Goal (SDG) (UN, 2015), which is driven by excessive anthropogenic carbon emissions. The concept of carbon neutrality typically refers to zero-carbon emission, also known as net-zero emission. It remains unclear whether a state of zero-carbon emission is possible. If so, how can carbon-dominated production systems and supply chains be transformed toward carbon neutrality? What will be the driving force and the catalysts for this transition? Carbon neutrality has become an urgent concern for economies, supply chains, and companies worldwide (Ghadge et al., 2020; Cao et al., 2023). Presently, all the countries across the globe strive to identify suitable strategies to reduce their carbon footprints and eventually achieve net-zero emissions. For example, Janet Napolitano, President, The University of California, announced the most ambitious program to conserve the environment in USA – Carbon Neutrality (Forgie and Carlson, 2018). On the other hand, Paris signed a petition to target net-zero emissions by 2050 to transform into a carbon-neutral city (Horowitz, 2016).

With the increment in the number of industries, vehicles, and households, overall energy consumption has grown. Large parts of energy are generated from carbon sources, greenhouse gas (GHG) emissions, and global warming (Sindhwani et al., 2022b). Carbon-neutral production and consumption patterns are the immediate solutions to resolve this issue (Waisman et al., 2019). Generally, organisations follow two practices to pursue carbon neutrality: i) growing trees to reduce the carbon content (carbon offsetting) and ii) applying suitable strategies to reduce GHG emissions. These two practices result in carbon footprint reduction (CFR) (Wang and Zhao, 2022). Several industrial giants have stepped into the net zero-emission initiatives and started following these popular approaches to retain a *'carbonneutral'* tag. For example, Patagonia envisaged gaining sustainability and quality priorities with a mission to "Build the best product, cause no unnecessary harm, use business to inspire and implement solutions to the environmental crisis" (O'Rourke and Strand, 2017). Walmart (2017) launched the Gigaton to embrace its business and supply chain in reducing its overall carbon footprints. Hewlett Packard has started using renewable energy sources and is predicted to operate on 100% clean energy by 2025 and have net-zero GHG emissions by 2040 to become carbon-neutral (Hewlett Packard, 2022). Danone, a world leader in the food industry, has aligned with the carbon neutrality mission of 2050 and follows a management strategy based on three critical pillars, namely  $- i$ ) Reduction: decreasing carbon emission to reduce carbon

footprint; ii) Sequestering: keeping carbon underground through different activities, such as agriculture, planting trees, and use of decarbonising agents and iii) Eliminating deforestation: deforestation is responsible for approximately 15% of carbon emissions. Danone is excluding deforestation within its supply chain (Danone, 2021).

Many industries are on the cusp of adopting zero-emission approaches and developing innovative solutions to mitigate environmental hazards regarding GHG emissions. Today, many fashion brands, including – Reformation, Kirkwood, and Allbirds are becoming carbonpositive and are certified carbon-neutral organisations (VOGUE, 2021). Allbirds, a leading shoe manufacturer, uses natural materials like sugarcane-based sweet foam to make the shoes carbon-neutral (Allbirds, 2022). Allbirds has made this innovation accessible to its competitors to make the entire industry more sustainable (Hobson and Hagan, 2019). Although effective in striving for sustainability and reducing carbon footprints, these approaches incur additional costs to organisations and burden the supply chains and overall business strategies (Mahapatra et al., 2021). These costs make organisations resist the strategic implementation of such initiatives.

One such industry that is a significant contributor to carbon footprints is the clothing industry, which includes the textile, garment, and apparel businesses. The clothing industry is the second most polluting industry after the oil and gas sector (Dohale et al., 2023b; Muthu, 2017). The toxic chemicals, water, and land in the production of clothes and the waste generated during the processes are the primary ingredients that negatively impact the environment and increase the carbon footprint (Muthu, 2019, 2017). It is estimated that 25% of the fabric is wasted during garment cutting and clothing production. This waste is usually incinerated or directly landfilled despite having the opportunity to recycle or reuse these byproducts (Dohale et al., 2023b; Muthu, 2017; Shukla, 2020). Ellen MacArthur Foundation (2016) has stressed that the major sectors contributing to GHG emissions, namely construction, clothing, food and agriculture, and automobile manufacturing, should be the first to implement sustainable and green practices to improve decarbonisation. It is predicted that implementing sustainability and green procedures in these industries can bring an annual benefit of approximately US\$ 624 billion, equivalent to 30% of the Indian GDP, and reduce around 44% of GHG emissions by 2050 in India (Muthu, 2019). These facts make the clothing industry increasingly aware of adopting practices aiming for carbon neutrality to become sustainable and stay competitive.

The existing literature suggests the need to adopt carbon neutrality practices by the clothing industry. In India, the clothing industry mainly comprises small and medium enterprises (SMEs). Previous studies reported that SMEs are facing issues in implementing sustainable and green practices to usher towards carbon neutrality due to scarcity of finance, unavailability of skilled workforce, appropriate governmental and legal actions, and lack of suitable technology (Álvarez Jaramillo et al., 2018; Karuppiah et al., 2020; Majumdar and Sinha, 2018). Thus, it is crucial to identify the critical determinants of carbon neutrality (CDs-CN) that may help the clothing industry reap the benefits and advantages of carbon neutrality practices to build a "carbon neutral" world in the coming future. Ultimately, the motivation for this study lies in the urgent need to create a more sustainable and environmentally responsible clothing industry, benefitting both the planet and its inhabitants.

This study attempts to achieve the purpose mentioned above by addressing the following research question (RQs):

- RQ 1. What critical determinants can assist in pursuing carbon neutrality in the clothing industry?
- RQ 2. Which determinants contribute the most to carbon neutrality in the clothing industry?
- RQ 3. How to evaluate the carbon neutrality index and find the best combination of critical determinants?

This study identifies and analyses the critical determinants of implementing carbon-neutral practices in the clothing industry. To accomplish this purpose, the present work utilised a twostage methodology comprising – multi-criteria decision-making (MCDM) based voting analytical hierarchy process (VAHP) and machine learning (ML) based Bayesian network (BN). We used transition management as a theoretical lens to determine and assess the role of CDs-CN in transforming net-zero emissions in the operations and supply chains of clothing industries. Initially, a total of 14 CDs-CN, including the group and sub-determinants, are identified through a comprehensive literature review. Based on the inputs received from 125 clothing industry experts, we computed each determinant's strength in achieving carbon neutrality using the priority weights of each CD-CN generated by the VAHP. After that, BN was used to predict the level of carbon neutrality achieved through a specific configuration of CDs-CN, referred to as the carbon neutrality index (CNI), in this study. Finally, a sensitivity analysis is performed to identify the most influential CDs-CN.

The remainder is structured as follows: A comprehensive review of carbon neutrality in operations and supply chain management research, the theoretical lens, and the CDs-CN are presented in Section 2. Section 3 describes the methodology used in this study in detail. Section 4 provides a discussion of the results. Section 5 discusses the theoretical and managerial implications of the present research and also provides recommendations relating to SDGs. Section 6 concludes by pointing to avenues of future research.

## **2 Theoretical Underpinning and Literature Review**

#### **2.1 Transition Management Theory**

Transition Management is a systematic planning process to execute the change within an organisation to achieve the desired future state without disturbing the existing business continuity. Transition is not a deterministic process and involves multiple challenges at different stages of change (Rotmans et al., 2001). Transition Management is a perpetual process that guides and provides insights regarding the essential steps and triggers organisations need for organisational change and its response (Buchanan and McCalman, 1989). Senior management, typically termed transition managers, play a pivotal role in the overall change process. This transition management process starts much earlier than the real organisational change. The transition management process is unique for different contexts, players, problems, and solutions. The transition management theory offers the basic ideology for effectively managing organisational transitions in an operational sense (Loorbach, 2010).

The transition management theory elucidates the governing and managing of overall sustainable transformations. Transition management theory is gaining popularity within sustainability research (Sarasini and Linder, 2018). Many researchers with environmental management and sustainability backgrounds use the transition management theory to demonstrate the key ideologies organisations must follow to bring green and sustainable changes. For example, Shankar et al. (2019) used transition management theory to identify and analyse the enablers of decarbonisation in the context of dedicated freight corridors for creating carbon-neutral freight transport. Kemp et al. (2007) adopted the transition management theory to analyse the sustainable development status for managing processes of co-evolution towards sustainability. Kumar (2021) used transition management theory to assess the critical practices for environmentally responsible transport systems to transform and usher towards sustainable freight transport.

The present study assesses how the clothing industry's carbon-dominated manufacturing and supply chain transforms into carbon neutral. Some specific attributes or determinants can aid the clothing industry in this transition. This study is based on analysing such attributes, i.e. critical determinants for achieving carbon neutrality within the context of the clothing industry. Hence, the transition management theory is well suited and helps understand the critical CDs-CN for bringing the transition to achieve a carbon-neutral clothing industry.

## **2.2 Carbon Neutrality**

Carbon neutrality, also known as net zero-emission since its announcement by Forgie and Carlson (2018), has become a trending topic in the management research fraternity. Carbon neutrality typically deals with *"ensuring the elimination or removal of produced warming gases and energies from the atmosphere in some other way with interim targets"* (Sindhwani et al., 2022b). Researchers are trying to establish novel concepts, some unique ideologies, and real-valued implicative solutions to demonstrate the practicality of carbon neutrality. The issues caused by climate change have triggered supply chain researchers to strategically rethink management tools and practices, including risk management (Ghadge et al., 2020). Hence, practitioners started assessing the overall environmental impact of their organisations on the carbon footprint – by computing GHG emissions to monitor progress toward SDG (de Sousa Jabbour et al., 2019; Mahapatra et al., 2021; Wang and Zhao, 2022; Zhang et al., 2022).

In the recently held 26th UN Climate Change Conferenc[e1,](#page-5-0) UK 2021 (COP26), emphasis was made on the urgent need to mitigate the global climate threats by reducing carbon emissions within organisations and their supply chains. The conference reignited the decarbonisation aspect and demanded strengthening the 'integrity of the private sector net-zero plan' (COP26, 2021). This illustrates the criticality of committing to carbon neutrality by firms rather than their commitments to focus on reducing carbon emissions.

Many global organisations have started strategizing carbon neutrality in their operations and supply chains by rethinking how their business models relate to societal and ecological systems and eventually impact the world's climate (Wannags and Gold, 2022). However, organisations that started developing ways to reduce GHG emissions witnessed that their supply chain networks overshadowed the direct emissions of organisations (Plambeck, 2012). Hence, it is

<span id="page-5-0"></span><sup>1</sup> <https://ukcop26.org/wp-content/uploads/2021/11/COP26-Presidency-Outcomes-The-Climate-Pact.pdf>

apparent that firms develop strategies for achieving carbon neutrality by considering their endto-end value chain (Gong et al., 2018; Zhang et al., 2022).

Clothing, one of the most sought-after products globally, strives to make its operations and supply chains more sustainable and, in turn, carbon neutral. Some of the frontrunner brands, namely – Patagonia, Pact, Quince, Kotn, and Reformation, have introduced sustainable practices in their manufacturing supply chains. However, many efforts are still needed to reach carbon neutrality. de Sousa Jabbour et al. (2019) state that the research on the concept of carbon neutrality is still at the nascent stage. The existing studies on carbon neutrality predominately take a macro perspective, highlighting the initiatives towards carbon neutrality at the global, regional, and national levels, mainly focusing on policy and technological aspects of carbon neutrality (Chen et al., 2022; Zhang et al., 2022). Apart from this, some studies have analysed the drivers of carbon neutrality (Zhang et al. (2022); Sindhwani et al. (2022b)). However, there is still a lacuna in the existing knowledge on understanding the critical determinants that help achieve carbon neutrality. While the strength of these determinants may vary from industry to industry, the clothing industry represents a revelatory application case for our analysis due to its significant carbon impact and extraordinary potential for improvement toward a net zeroemission. In the following section, the CDs-CN are reviewed and described.

#### **2.3 Critical Determinants of Carbon Neutrality**

We utilised a systematic literature review (SLR) method to determine the CDs-CN. The existing literature is investigated thoroughly to identify relevant and critical research articles. Major academic databases, including – Scopus, web of science, google scholar, pro-quest, and EBSCOhost, were searched iteratively to obtain relevant research articles. We utilised two keyword clusters – 1) related to carbon neutrality, such as – "carbon neutrality", "net zero", "decarbonisation", "green practices", "sustainable practices", "climate neutrality", and 2) related to critical determinants as "factors", "determinants", "enablers", in the title/abstract/keywords field. These keywords are combined using Boolean operators (AND/OR). Keywords from the same clusters are combined using OR operator, while the different cluster keywords are coupled with AND operator. The initial search produced a sample of 576 relevant articles.

Further, we excluded the articles that were either duplicated, not matching the study theme, and article type of erratum, notes, corrigendum, or written in a language other than English. Finally, we obtained 59 research articles that were critically examined to retrieve the critical determinants of carbon neutrality. We identified 14 relevant CDs-CN, including the group determinants and sub-determinants.

We used a validatory survey method to check the relevance and relatability of the identified CDs-CN in the context of the clothing industry using experts' opinions. We initially contacted 205 experts to validate the CDs-CN. Out of these, 125 experts participated in the validatory survey with a response rate of 51%. Previous studies mentioned that a response rate higher than 20% is suitable for gaining valuable insights into the problem through surveyed data (Dohale et al., 2023a; Majumdar et al., 2021; Malhotra and Grover, 1998). The details of the questionnaire, responses, and profile of participants are provided in Appendix I, II and III. The experts were asked to assign scores to the identified CDs-CN based on their relevance using the five-point Likert scale (Strongly Disagree  $= 1$ ; Strongly Agree  $= 5$ ). CDs-CN having an overall score of 3.0 and above, were retained for the study. The CDs-CN were classified into three group determinants (A total of 14 CDs-CN), as presented in Table 1.

#### **2.3.1 Managerial Determinants (C1)**

Organisations rely on the support of the top management team, including leaders and managers who encourage and take charge of the "carbon neutrality" mission, to get results from energyefficiency projects (van Sluisveld et al., 2017). This results in a staggered and unstable approach toward implementing sustainable and green practices. Companies need a skilled workforce, adequate technological support, and sufficient funds to drive these practices and achieve decarbonisation. The managerial determinants are oriented toward the assistance required to build the infrastructure for bringing the transformation of carbon neutrality, including – technological support, professional expertise, and adequate financial aid (Ağbulut et al., 2021; Sindhwani et al., 2022b; Zhang et al., 2022).

#### **2.3.2 Green and Sustainable Determinants (C2)**

The adoption of green and sustainable practices by organisations can help them to reduce their harmful impact on the environment (Ambilkar et al., 2023). This means that organisations should adopt ecologically sustainable actions in their business activities (Koirala et al., 2016). Sustainable and green innovations can help achieve net-zero emission and decarbonisation (Bai et al., 2022; Sindhwani et al., 2022b). Green and sustainable determinants involve the availability of decarbonising techniques and practices required for pollution & waste management, carbon offsetting, and eco-energy stability.

## **2.3.3 Government and Legal Determinants (C3)**

The government's role in imparting and implementing new policies toward environmental sustenance is well articulated in the literature. There should be an enforcement mechanism built by an international Government community to implement strict legal and ecological norms at the local, state, national, and international levels (Huang et al., 2021; Sudarsan et al., 2022). Due to the issues involved in governmental organisations' intra- and inter-departmental coordination, the propagation of rules and regulations is constrained. This results in a lack of awareness among business organisations with updated regulatory initiatives and actions (Bai et al., 2022).

# Table 1. Description of CDs-CN





## **3 Research Methodology**

In this research work, an integrated VAHP – BN framework is deployed to explore and analyse the CDs-CN. The detailed methodological framework adopted in this study is presented in Figure 1. The complete details about the VAHP and BN methods are provided next.



Figure 1. Methodological Roadmap

## **3.1 Voting Analytical Hierarchy Process**

The MCDM techniques best fit when the evaluation includes the criteria or factors with varying natures and comprises inherent trade-offs among the criteria (Dohale et al., 2021a; Ghuge et al., 2022; Mardani et al., 2015). In the existing body of knowledge, dozens of MCDM methods exist, such as – AHP, ANP, TOPSIS, DEMATEL, ISM, and VIKOR. Some authors have developed extensions of these methods by combining them with fuzzy sets, rough sets, and neutrosophic sets (Dohale et al., 2022b; Kahraman et al., 2015; Mardani et al., 2015). Despite the promising utility of these MCDM methods and their extensions in solving complex problems, these methods are unreliable due to data imprecision, subjectivity, limitation to deploy a large set of experts for evaluation, and uncertainty in the produced results (Belhadi et al., 2022). Apart from these limitations, one major issue reported in the existing literature about MCDMs is the lack of mathematical evidence to support the results.

We have utilised a VAHP technique in this study. VAHP was developed by Liu and Hai (2005), comprising a mathematical formulation to address MCDM problems, and has been applied to sustainability problems such as sustainable supplier selection (Pishchulov et al., 2019). This method is a mathematical extension of AHP and outperforms AHP and other MCDM methods. VAHP utilises linear programming based "S*trong Ordering Data Envelopment Analysis (SO-DEA)"* proposed by Noguchi, Ogawa, and Ishii (2002) for calculating the weights of attributes under evaluation. Thus providing robust mathematical support for the weight calculations (Dohale et al., 2022a; Laguna-Sánchez et al., 2020). Also, the other MCDM techniques and AHP forms can deploy a maximum of 10-15 experts, which depicts the lack of retaining the expertise in a broader range. In VAHP, a sample of more than 100 experts can be analysed for criteria evaluations. Further, VAHP comprises a comparatively easy and less iterative vote ranking method to evaluate and prioritise criteria, unlike the pairwise comparison (Soltanifar and Hosseinzadeh Lotfi, 2011). These reasons lay a strong justification for using VAHP instead of other MCDM methods in the present study. In VAHP, the attributes are voted at different places to generate rank voting data (Hai and Liu, 2007; Liu and Hai, 2005; Mahammedi et al., 2022). After that, by utilising SO-DEA, the priority weights of criteria under evaluation are computed using the rank voting data (Ayyildiz and Taskin Gumus, 2021; Laguna-Sánchez et al., 2020; Soltanifar and Hosseinzadeh Lotfi, 2011). In this work, we utilised VAHP to evaluate the priority weights of the CDs-CN to prioritise them to determine the significant ones. The experts voted for the CDs-CN assigning different ranks depending on their strength and importance. The evaluation is carried out using the SO-DEA formulation. The details of SO-DEA are provided next.

Let us assume there are total  $n$  voters (respondents) deployed for ranking the attributes. Every respondent ranks each of the CDs-CN at different places from 1 to P, and  $P \leq C$ , where P is the number of total ranking places, and  $C$  is the total CDs-CN. As mentioned earlier, VAHP offers an additive advantage to researchers to have a large number of experts for the evaluation process that can range from 8 to 60 (Dohale et al., 2021b). At the same time, it is observed in the literature that some existing studies utilised experts beyond this range. For example, Ayyildiz and Taskin Gumus (2021) used 100 respondents to evaluate the distance learning risks using VAHP. Dohale et al. (2022a) assessed the critical success factors of implementing artificial intelligence for enhancing production resilience using 120 experts. So, VAHP is featured as a technique to handle big data for evaluation effectively. Thus, even if a range of 8 to 60 is adequate, researchers may include more experts to conduct a finer evaluation.

Selecting the right voters or respondents with adequate expertise is crucial as the results rely on the experts' know-how. Hence, we utilised four critical expert selection criteria to retain suitable respondents/voters  $- i$ ) Since the research is related to the clothing industry, experts shall be working for a clothing and its allied industries; ii) knowledge about carbon neutrality and its associated activities; iii) Experience of at least five years in the area of carbon emission reduction, green and sustainable practices; and iv) Interest to participate in the study (Bokrantz et al., 2017). Following these four criteria, 125 respondents were shortlisted for conducting VAHP in this study. We collected the ranking data from 1[2](#page-13-0)5 voters (respondents)<sup>2</sup>. The ranking data is shown in Table 2. The ranking data is fed to the SO–DEA model. The SO–DEA model is explained next.

Here,  $W_{cc}$  is the weighted sum of votes received by  $c<sup>th</sup>$  attribute, P is the total number of ranking places (where,  $P \le C$ ). C in this study is the total number of CDs-CN,  $w_{cp}$  represents the weight of the  $p<sup>th</sup>$  place concerning the  $c<sup>th</sup>$  CDs-CN, and  $V_{cp}$  denotes total votes given by *n* voters to  $c<sup>th</sup>$  CDs-CN at the  $p<sup>th</sup>$  place.  $\varepsilon$  in equation (1) signifies the discriminating factor. It represents the difference in weights between criteria placed at  $p^{\text{th}}$  place and  $(p + 1)^{\text{th}}$  place. In the robust ordering method by Noguchi, Ogawa, and Ishii (2002),  $\varepsilon$  i.e. difference in weights between  $p^{\text{th}}$ place and  $(p + 1)$ <sup>th</sup> is kept more than zero. Since, there should be a small and progressive increment in the weights so that the difference between the weight of the first place criterion and the last place criterion should be optimal, the value of  $\varepsilon$  is adjusted according to the number of votes and the places (Liu and Hai, 2005; Noguchi et al., 2002).

<span id="page-13-0"></span><sup>&</sup>lt;sup>2</sup> The detailed profile of sampled respondents is provided in the Appendix I

$$
W_{cc} = \max \sum_{p=1}^{P} w_{cp} V_{cp}
$$
  
Subjected to,  

$$
W_{cx} = \sum_{p=1}^{P} w_{cp} V_{cx} \le 1 \quad (x = 1, 2, ..., C)
$$

$$
w_{c1} \ge 2w_{c2} \ge 3w_{c3} \ge ... \ge Pw_{rp}
$$

$$
w_{cp} \ge \varepsilon > 0
$$

$$
\varepsilon = \frac{2}{\{n \times P(P + 1)\}}
$$
 (1)

Table 2. Rank Voting Data









The relative weights of all the CDs-CN are computed using equation (1). The averaging method is utilised to normalise the relative weights. The global weights are calculated by multiplying the normalised weights of group criteria with the normalised weight of sub-criteria. Further, the CDs-CN are ranked based on normalised weights to understand their significance, as shown in Table 3.

Group Determinants	The relative weight of Group Determinants	Normalised weight of Group Determinants $(W_g)$	Sub Determinants	The relative weight of Sub Determinants	Normalised weight of Sub Determinants $(W_s)$	Global Weights $(W_g \times$ $W_s$ )	Priority Ranks
C <sub>1</sub>			C11	0.8621	0.3091	0.1033	6
	1.0000	0.3341	C12	1.0000	0.3586	0.1198	
			C13	0.9267	0.3323	0.1110	$\overline{4}$
C <sub>2</sub>			C <sub>21</sub>	0.7999	0.1749	0.0584	11
	1.0000	0.3341	C <sub>22</sub>	0.8593	0.1879	0.0628	10
			C <sub>23</sub>	1.0000	0.2187	0.0731	7
			C <sub>24</sub>	0.9315	0.2037	0.0681	9
			C <sub>25</sub>	0.9822	0.2148	0.0718	8
C <sub>3</sub>			C <sub>31</sub>	0.9839	0.3412	0.1132	3
	0.9932	0.3318	C <sub>32</sub>	0.9000	0.3121	0.1036	5
			C <sub>33</sub>	1.0000	0.3468	0.1151	$\overline{2}$

Table 3. Priority Weights of CDs-CN computed using VAHP

## **3.2 Bayesian Network (BN)**

BN is a complex decision-making and prediction tool that falls under the ML-based statistical operations tool (Dohale et al., 2022a; Hosseini et al., 2020). Researchers have predominantly used BN for solving intricate problems consisting of uncertainty (Hosseini et al., 2020; Hosseini and Barker, 2016a). BN follows Bayes's theorem and is based on statistical learning theory (Castillo et al., 1997). BN graphically shows the probabilistic interlinks between the attributes (Wuest et al., 2016). In BN, the directed acyclic graphs (DAG) are used to model the probabilistic interdependencies between the two attributes, viz. variables, factors, risks, etc. DAG consists of various nodes connected through arcs. The attributes are represented through nodes, while the probabilistic dependencies between attributes are shown using the arcs (Hosseini et al., 2020; Hosseini and Ivanov, 2021). A Conditioned Probability Table (CPT) or Node Probability Table (NPT) is assigned to every node to define the conditional probabilities of the attribute.

BN possesses certain additive benefits over other ML techniques, such as  $- i$ ) BN evaluates attributes with a qualitative and quantitative nature; ii) Even with limited data, BN effectively solves the problem under study; iii) It provides an ability of rigorous learning; and 4) The outputs of BN are easily understood and interpretable (Hosseini and Sarder, 2019). BN can capture the strength of interrelationships more efficiently than the other graphical approaches, namely, social network analysis, DEMATEL, and interpretive structural modelling (ISM) (Kamble et al., 2021). Furthermore, BN can effectively conduct what-if analysis to understand the impact of change in the probability of parent or input node attributes over the output or target node (Hosseini and Barker, 2016a; Sharma and Rai, 2020).

In this study, we evaluated and predicted the impact of CDs-CN on carbon neutrality and determined the most influential CDs-CN in achieving carbon neutrality. This work attempts to determine how each CDs-CN influences carbon neutrality by computing the CNI using BN. Hence, in this study, the target or output node is set as the carbon neutrality index, while the 14 CDs-CN are the input nodes. The prior probabilities of attributes are used as input to develop a problem. The data for prior probabilities of nodes can be retained through system-generated real data or expert surveys (Dohale et al., 2021b; Wuest et al., 2016).

In this research, the data for the prior probabilities of the nodes, i.e., CDs-CN, is collected through a survey using the shortlisted 125 respondents deployed for VAHP and a validatory survey. Having similar experts for both methods helps to maintain consistency in the opinions. The survey comprises the question related to the influence of CDs-CN on the carbon neutrality index. For example, "At what level does 'Professional Expertise (C12)' influence the carbon neutrality index?" The experts were asked to provide their responses over a six-point Likert scale  $(1 - Extremely Low (EL); 2 - Very Low (VL); 3 - Low (L); 4 - High (H); 5 - Very High)$  $(VH)$ ; 6 – Extremely High (EH). The experts' responses were classified into two categories – Low (L, VL, and EL) and High (H, VH, and EH). Based on the experts' responses, the probabilities of the influence of CDs-CN were determined into the Low and High categories. For example, the responses received for 'professional expertise  $(C12)$ ' CSF are  $-$  26 (EH), 78 (VH), 19 (H), 2 (L), and 0 for both (VL) and (EL). This implies that  $123$  (26+78+19) out of 125 experts prefer high values while the remaining 2 prefer low values. Thus, the probabilities of high and low values are computed as:  $\left(\frac{123}{125}\right) = 0.984$  and  $\left(\frac{2}{125}\right) = 0.016$ , respectively. Similarly, the prior probabilities of all the other CDs-CN are computed in high and low categories<sup>[3](#page-16-0)</sup>. The prior probabilities are used to develop a BN model. In this study, we deployed the GeNIe package, one of the most utilised software for building the BN model. Simplicity in working in the GeNIe platform, handling complex problems with a large volume of data, and

<span id="page-16-0"></span><sup>&</sup>lt;sup>3</sup> The survey for generating prior probabilistic data of BN is provided in the Appendix III.

the ability to generate precise results are the forte and noteworthy advantages of GeNIe. Figure 2 illustrates the BN developed using GeNIe.

Further, the influence of CDs-CN over the CN is predicted using what-if analysis. We evaluated the impact of high and low probabilities of each CDs-CN over the achievement of CNI. Table 4 presents the results of the effects of change in conditional probabilities over the CNI.

#### **4 Results and Critical Discussions**

As discussed in Section 2, from the extensive systematic review, it is observed that most of the studies on carbon neutrality are qualitative and assess the initiatives, policies, or inquiries of the technological interventions toward carbon neutrality. However, the present research is novel in using MCDM-ML methods to unfold a quantifiable horizon of results regarding the influential determinants of carbon neutrality. This section critically discusses the results obtained through VAHP (MCDM) and BN (ML) methods. We carried out the strength of influence analysis and sensitivity analysis, as shown in Figures 3 and 4, respectively, to understand the influence of prominent CDs-CN in achieving carbon neutrality and validating the robustness of the model and results. The results of this study are critically analysed and compared with the existing studies to demonstrate their relevance to the current agenda of carbon neutrality.

#### **4.1 VAHP**

We have utilised MCDM-based VAHP to compute the relative weights of CDs-CN. The CDs-CN are ranked based on the global weights, as illustrated in Table 3. The VAHP assessment unfolds some critical findings in this study. In the group determinants, managerial (C1) and 'green and sustainable practices' (C2) received a maximum weight of 0.3341. As discussed earlier, managerial determinants are critical to brainstorming unique ideas for carbon neutrality achievement and planning the execution of these ideas within the organisation. Providing the appropriate solution and optimally directing the resources to achieve the desired carbon-neutral goals are crucial roles for managers (Sindhwani et al., 2022b). In most cases, organisations possess the required understanding but lack appropriate management strategies for driving decarbonisation through their operations and supply chains.



Figure 2. Bayesian Network (Carbon Neutrality) – GeNIe

Managerial (C1) C1			<b>Green and Sustainable Practices (C2)</b>					C <sub>2</sub>		<b>Government and Legal</b> (C3)		C3		<b>Carbon Neutrality Index</b> (CNI)			<b>CNI</b>				
<b>C11</b>	C12	C13	L	$\mathbf H$	C <sub>21</sub>	C <sub>22</sub>	C <sub>23</sub>	C <sub>24</sub>	C <sub>25</sub>	L	$\mathbf H$	C31	C32	C33	L	$\mathbf H$	C1	C2	C <sub>3</sub>	L	$\mathbf H$
L	L	L	1.000	0.000	L	$\mathbf{L}$	L	L	L	0.999	0.001	L	L	L	0.990	0.010	L	L	L	1.000	0.000
L		H	0.900	0.100	L	L	L	L	H	0.980	0.020	L	L	H	0.850	0.150	L	L	$\rm H$	0.930	0.070
L	H	L	0.500	0.500	L	L	L	H	L	0.950	0.050	L	H	L	0.950	0.050	L	H	L	0.750	0.250
	H	H	0.300	0.700	L	L	L	$\, {\rm H}$	$\, {\rm H}$	0.945	0.055	L	H	H	0.800	0.200	L	H	$\, {\rm H}$	0.350	0.650
H			0.800	0.200	L		H		L	0.935	0.065	H	L	L	0.550	0.450	H	L	L	0.750	0.250
H		H	0.700	0.300	L		H		$\, {\rm H}$	0.600	0.400	H	L	H	0.050	0.950	H	L	$\rm H$	0.200	0.800
H	H		0.600	0.400	L		H	$\, {\rm H}$	L	0.800	0.200	H	H	L	0.150	0.850	H	H	L	0.012	0.088
H	H	H	0.000	1.000			H	H	H	0.570	0.430	H	H	H	0.000	1.000	H	H	$\rm H$	0.000	1.000
					L	H	L	L	L	0.920	0.080										
					L	H	L	L	$\, {\rm H}$	0.725	0.275										
					L	H	L	$\rm H$	L	0.650	0.350										
					L	H	L	H	$\, {\rm H}$	0.695	0.305										
					L	H	H	L	L	0.650	0.350										
						H	H		$\, {\rm H}$	0.175	0.825										
					L	H	H	$\, {\rm H}$	L	0.550	0.450										
					L	H	H	H	$\, {\rm H}$	0.150	0.850										
					H	$\mathbf I$	L		L	0.800	0.200										
					H		L		$\, {\rm H}$	0.750	0.250										
					H	L	L	H	L	0.825	0.175										
					H	L	L	$\, {\rm H}$	$\, {\rm H}$	0.715	0.285										
					H	L	H	L	L	0.700	0.300										
					H	L	H	L	$\, {\rm H}$	0.350	0.650										
					$\, {\rm H}$	L	H	$\, {\rm H}$	L	0.625	0.375										
					$\, {\rm H}$	L	H	H	H	0.075	0.925										
					H	H	L	L	L	0.550	0.450										
					$\, {\rm H}$	H	$\mathbf{L}$	L	$\, {\rm H}$	0.515	0.485										
					H	H	L	H	L	0.550	0.450										
					$\, {\rm H}$	H	L	$\, {\rm H}$	$\, {\rm H}$	0.275	0.725										
					$\, {\rm H}$	H	H	L	L	0.345	0.655										
					$\, {\rm H}$	H	H		$\, {\rm H}$	0.195	0.805										
					H	H	H	H	L	0.325	0.675										
					H	H	H	H	H	0.999	0.001										

Table 4. Impact of conditional probabilities of CDs-CN over Carbon neutrality index (CNI)

Hence, the managers must have adequate professional expertise and know-how about carbon neutrality practices. The results from VAHP also validated this statement as, in terms of subdeterminants, professional expertise (C12) ranked 1 in terms of influential CDs-CN. Considering the green and sustainable practices determinants, good insights to the management about the different available initiatives to achieve the carbon neutrality goal are critical. Green and sustainable practices (GSPs) are becoming popular among clothing industries, and many industrial giants are following these GSPs. GSPs involve environment-friendly techniques within the operations and supply chain, which can help achieve a sector's overall sustainable development goals (Oelze, 2017; Wang and Zhao, 2022). Such GSPs require trained human resources and adequate financing. The government and legal determinants are equally important to meet the overall net-zero emission agenda. The government's involvement in communicating and imposing different GSP initiatives and their legal aspects is crucial. The strategic role of government and legal norms in establishing the standards supporting environmental wellness is well established in the literature (Govindan et al., 2016; Muthu, 2019).

Considering the sub-determinants level, the results from VAHP depict that professional expertise (C12) received the highest weight (0.1198) amongst all the CDs-CN, as shown in Table 3. Followed by C12, the other CDs-CN on the top of the lists are - Green Supply Chain Initiatives (C33) (0.1151) > Laws and Certifications (C31) (0.1132) > Financial Investment for Net Zero Initiative  $(C13)$   $(0.1110)$  > Short-Term Targets  $(C32)$   $(0.1036)$  > Technological Acceptance (C11)  $(0.1033)$  > Availability of Decarbonizing Methods (C23)  $(0.0731)$  > Adequate Carbon Offsetting (C25) (0.0718).

Any concept can be effectively implemented if it receives the necessary support in the form of professional expertise. GSPs essentially depend on the knowledge of experts leading the implementation of these initiatives (Shankar et al., 2019; Sindhwani et al., 2022a). Additionally, the literature suggests that a lack of professional expertise affects the effective implementation of green and sustainable practices, including carbon reduction practices (Sindhwani et al., 2022b). Furthermore, laws and certifications are the other facets that should be commenced along with the green supply chain initiatives. The laws and certifications are crucial drivers and facilitators of green supply chain initiatives (Dohale et al., 2023a; Govindan et al., 2016). Once policies are converted into mandatory laws, manufacturers feel pushed to substantially transform their activities in line with GSPs (Govindan et al., 2016; Majumdar and Sinha, 2019). Further, certifications exert helpful guidance to managers in establishing appropriate green supply chain initiatives (Tumpa et al., 2019).

Sufficient finance for investing in net zero emission strategies is crucial. Unless and until adequate funds are available, the GSPs and decarbonisation initiatives keep struggling. Industries seek help from the government as a funding body to provide subsidies for moving toward GSPs. Further, government support in the form of incentives to frontrunner clothing companies can also encourage the other players in the clothing industry to the carbon-neutral transition. Staff is often reluctant to change due to various fears, such as job loss. The appropriate change management principles may prepare the ground for transformative decarbonisation-related technologies to get accepted by the staff. Global organisations are seeking new technological interventions, particularly Industry 5.0. Industry 5.0 is conceived as more sustainable and resilient<sup>[4](#page-21-0)</sup>, where interactive human-machine platforms can develop (Dohale et al., 2023a; Ghobakhloo et al., 2022). Since Industry 5.0 is more man-machinecentric, it can help resolve the issue due the fear of unemployment.

Further, decarbonisation deals with developing methods that help scrap carbon dioxide off. Carbon offsetting is related to developing *"processes of compensating for carbon dioxide emissions arising from industrial or other human activity by participating in schemes designed to make equivalent reductions of carbon dioxide in the atmosphere."* The availability of decarbonising and carbon offsetting techniques are the core CDs-CN to achieve carbon neutrality.

## **4.2 Bayesian Network and Sensitivity Analysis**

In this study, BN is adopted to compute the influence of each of the CDs-CN on the overall achievement of carbon neutrality. We assessed the impact of the different settings of CDs-CN on the CNI. As discussed in the previous section, we used GeNIe software to construct the BN model. Figure 2 shows a BN model for one of the possible combinations of CDs-CN and the achieved probabilistic carbon neutrality index – High =  $0.91$  and Low =  $0.09$ . We computed the carbon neutrality achieved with the various settings of CDs-CN using what-if analysis and enlisted in Table 4. To get a more explicit understanding of the influential CDs-CN, we evaluated the strength of influence of CDs-CN, as shown in Figure 3. The strength of influence diagram of CDs-CN shown in Figure 3 depicts Professional Expertise (C12), Laws &

<span id="page-21-0"></span><sup>4</sup>[https://research-and-innovation.ec.europa.eu/news/all-research-and-innovation-news/industry-50-towards](https://research-and-innovation.ec.europa.eu/news/all-research-and-innovation-news/industry-50-towards-more-sustainable-resilient-and-human-centric-industry-2021-01-07_en)[more-sustainable-resilient-and-human-centric-industry-2021-01-07\\_en](https://research-and-innovation.ec.europa.eu/news/all-research-and-innovation-news/industry-50-towards-more-sustainable-resilient-and-human-centric-industry-2021-01-07_en)

Certification (C31), and Availability of Decarbonizing Methods (C23), which are the most influential CDs-CN which have a significant effect on the carbon neutrality index in the context of the clothing industry. The finding of the influence diagram supports the results obtained from VAHP.



Figure 3. CDs-CN Influence Diagram using BN

Furthermore, we conducted a sensitivity analysis to validate the robustness of the BN model. Sensitivity analysis is a practical approach that helps validate an expert-built model. Sensitivity analysis assesses the variation that occurred with the model's outcome with the changes in input parameters (Hosseini and Barker, 2016a). The influential attributes within the model can be easily identified and analysed using sensitivity analysis. Sensitivity analysis validates the replicability of the model and gains confidence in replicating it in future research (Dohale et al., 2022a; Hosseini and Barker, 2016b).

GeNIe has the provision to conduct the sensitivity analysis and display the sensitivity analysis results in a Tornado graph (GeNIe, 2022). This study quantifies the impact of 14 CDs-CN (including group and sub-determinants) on the carbon neutrality index using BN. Thus, the 14 CDs-CN are kept as sensitive nodes to check their influence over the carbon neutrality index, which is set as the target node in GeNIe, as shown in Figure 2. Figure 4 portrays the sensitivity analysis. Each bar represents the CDs-CN considered in this study. The bar length indicates the influence of determinants over the carbon neutrality index (Dohale et al., 2021b; GeNIe, 2022). As evident from Figure 4, 'professional expertise, technological acceptance, and laws and certifications' are the influential CDs-CN. These results are supported by findings from VAHP and strength of influence analysis.



Figure 4. Sensitivity Analysis

## **4.3 Recommendations through SDGs Lens**

The present study offers meaningful recommendations in line with the United Nation's sustainable development goals (SDGs). The SDGs are "*the blueprint"* as defined by the UN developed to build a better and more sustainable future for everyone (UN, 2020). These recommendations aligned with the SDGs can be useful for the clothing industry to achieve carbon neutrality while promoting responsible consumption and production, decent work, innovation, and climate action. The results of this research align with a list of SDGs, including – SDG 4, SDG 9, SDG 12, SDG 13, and SDG 17. The details are as follows –

## **4.3.1 SDG 4 – Quality Education**

This study aligns with SDG 4 in a manner to enhance consumer awareness and educate them about the environmental impact of their clothing choices. As mentioned, through green supply chain initiatives (C33), promoting awareness campaigns on sustainable fashion practices, ethical consumption, and the importance of supporting brands with strong environmental and social commitments will support manufacturing supply chains in moving towards carbon neutrality.

#### **4.3.2 SDG 9 – Industry, Innovation, and Infrastructure**

The recommendations related to SDG 9 are  $-1$ ) introduction of energy-efficient and more ecofriendly (C21) manufacturing processes in the clothing industry; 2) investment in technologies (C11) that reduce water and energy consumption, minimise waste, and lower greenhouse gas emissions to build a carbon-neutral clothing industry; and 3) identifying sustainable and innovative design practices in the clothing industry (C2).

#### **4.3.3 SDG 12 – Responsible Consumption and Production**

The recommendations with the aim of SDG 12 are  $-1$ ) embrace circular fashion to encourage circular economy practices in the clothing industry by promoting recycling, repair, and resale (C24); 2) ponder take-back programs and offer incentives to consumers on returning old clothing items for recycling; and 3) encourage consumers to make environmentally conscious choices by providing information on sustainable products and their benefits.

#### **4.3.4 SDG 13 – Climate Action**

In terms of SDG 13, the present study delves into sustainable practices  $(C2)$  to reduce climate impact by  $-1$ ) reducing carbon emissions in manufacturing supply chains by optimise transportation and logistics to reduce the carbon footprint; 2) exploring sustainable transportation options, such as low-emission vehicles and efficient supply chain management practices; and 3) regularly monitoring the progress towards carbon reduction targets.

#### **4.3.5 SDG 17 – Partnerships for the Goals**

In line with SDG 17, we also recommend that collaboration among clothing industry stakeholders, including manufacturers, retailers, NGOs, and government bodies, be fostered. Competitors should jointly work together to develop and implement initiatives that address carbon neutrality, collaborate best practices, and drive industry-wide change. Organisations must communicate their successful practices similar to Allbirds as a coopetitor to achieve carbon neutrality with their competitors (Allbirds, 2022).

#### **5 Research Implications**

This research work offers significant contributions to the existing literature on carbon neutrality and managerial implications for practitioners within the clothing industry. The theoretical and practical implications are given below.

#### **5.1 Theoretical and Methodological Implications**

The current study makes the following theoretical and methodological contributions to the stateof-the-art literature. Although the literature on carbon neutrality has amply discussed conceptual advancements of strategies for net-zero emission, theoretical frameworks, barriers, and enablers; determining the critical determinants of carbon neutrality for achieving net-zero emission goals within operations and supply chains is still in its infancy. The present study has, firstly, contributed to filling this literature gap. Secondly, this study is one of the earliest approaches that have identified the critical determinants of carbon neutrality (CDs-CN) and evaluated the influence of CDs over carbon neutrality achievement. Thirdly, this study complements insights from existing studies, namely — Shankar et al. (2019), Chen and Jang (2022), Sindhwani et al. (2022b), Wang and Zhao (2022), and Zhang et al. (2022) and identifies some unique critical determinants like adequate carbon offsetting and availability of decarbonisation techniques that can enhance the overall carbon neutrality index and guide businesses to implement carbon neutrality in their organisations. Finally, a noteworthy methodological contribution to the literature on operations research is the application of the integrated VAHP–BN methodology. Existing studies have proved that combining ML techniques with MCDM methods strengthens the computation and helps overcome MCDM methods' shortcomings (Dohale et al., 2022a; Kaya et al., 2023). Further, the

combination of ML-MCDM is extremely suitable while handling intricate problems with a big dataset.

#### **5.2 Managerial Implications**

This research can provide introductory guidance for practitioners working in the clothing industry and willing to engage with carbon neutrality practices regarding the question of which determinants are critical and most influential. Managers may foster significant determinants in their organisations in a targeted manner to successfully execute and achieve decarbonisation and net-zero emission practices within their operations and supply chains. Practitioners and managers who have started utilising carbon neutrality practices can re-examine and rethink their operations and supply chain strategies and conduct audits using the identified CDs-CN. This helps the practitioners compare the carbon neutrality index achieved at their organisations with the present study's findings. This will help them comprehend the possible improvements in influential CDs-CN for attaining an optimal CNI. We postulate that beyond optimising the carbon neutrality index, the present study can also be helpful to practitioners to achieve operational excellence more generally through the interventions of sustainable and green practices in their operations and supply chain. Thus, practitioners can align their business according to the influential CDs-CN to acquire the desired sustainable business goal.

## **6 Conclusion and Future Research**

Carbon neutrality by 2050 is called the world's most urgent mission by the United Nations owing to harm caused to the global climatic conditions through anthropogenic activities, currently and prospectively. Many nations have actively participated in this ambitious initiative of becoming carbon neutral by 2050. Many Governmental institutions have been developing strategies for carbon neutrality. Still, academia and practitioners have primarily not addressed how to implement carbon neutrality on a business and supply chain level. Against this backdrop, the present research investigates the critical determinants that need to be considered for becoming a carbon-neutral organisation. This research complements literature in the domain of not only environmental management but also operations and supply chain sustainability. This study offers novel insights into the CDs-CN in the context of the clothing industry through a quantitative methodological approach.

In doing so, this study attempts to address the research questions mentioned in Section 1. Addressing RQ 1, we conducted a systematic literature review to identify the critical determinants of carbon neutrality (CDs-CN). After scrutinising the extant literature thoroughly, we arrived at the set of 14 CDs-CN, including group and sub-determinants. To test the relevance of the identified 14 CDs-CN, a validatory survey is conducted using 125 experts from the clothing industry. All 14 CDs-CN are validated and retained for analysis. These determinants span a range of factors, from professional expertise to financial investments and green supply chain initiatives, all of which play a pivotal role in achieving carbon neutrality. We used MCDM based VAHP method for answering RQ 2.

Using VAHP, the relative weights of CSFs are computed by deploying 125 experts. We utilised the same experts for every evaluation to maintain consistency in the experts' judgments. According to the computed global weights of CDs-CN using VAHP, they are ranked and prioritised to determine the most significant CDs-CN. After that, we deployed machine learning-based BN to understand and learn the influence of the level of CDs-CN (High/Low) on carbon neutrality. For the same, we computed the CNI using BN. A what-if analysis is performed to understand the impact of different settings of CDs-CN on the overall achievement of CNI. We also examined the strength of influence of each critical determinant towards achieving carbon neutrality. Finally, the sensitivity analysis is conducted to validate the robustness of the BN model and its findings.

The finding from the analysis depicts that 'professional expertise (C12), laws and certifications (C31), technological acceptance (C11), availability of decarbonising methods (C23), adequate carbon offsetting (C25), green supply chain initiatives (C33), Financial Investment for Net Zero, and Initiative (C13), and Short-Term Targets (C32)' are profoundly the most influential CDs-CN that strongly impact carbon neutrality execution in the clothing industry. As the earlier study, this can act as a roadmap for practitioners and academicians to gain deeper insights into the role of CDs-CN in achieving carbon-neutral operations and supply chains in the clothing industry. The results of the study are discussed in relation to the UN's SDGs to offer recommendations to the clothing industry professionals.

This study offers directions for conducting future research. This study pertains to the analysis of CDs-CN in the clothing industry context. So, the findings may be confined to the clothing industry. While our study focuses on the clothing industry, the applicability of these determinants may vary

across different industries. Therefore, prospective researchers can explore CDs-CN in diverse sectors to gain a comprehensive understanding of their influence on carbon neutrality. Further, we hypothesise that the level of influence of CDs-CN over carbon neutrality achievement may vary from industry to industry. Thus, prospective academicians and practitioners can investigate the CDs-CN in different sectors. It is observed that resilience and sustainability are the aspects comprising trade-offs. Some recent unanticipated disruptive events, such as COVID-19 or the Suez Canal incident, have highlighted the prominence of resilience in supply chains (Dohale et al., 2023c). Thus, it would have been a concern for researchers globally to create a bridge between resiliency and sustainability for achieving a 'resilient-carbon neutral' operations and supply chain. Our study provides valuable insights for the clothing industry and opens doors to further exploration of carbon neutrality determinants and their intersection with resilience and sustainability across various sectors.

#### **References**

- Abdullah, L., Goh, P., 2019. Decision making method based on Pythagorean fuzzy sets and its application to solid waste management. Complex Intell. Syst. 5, 185–198. https://doi.org/10.1007/s40747-019-0100-9
- Ağbulut, Ü., Ceylan, İ., Gürel, A.E., Ergün, A., 2021. The history of greenhouse gas emissions and relation with the nuclear energy policy for Turkey. Int. J. Ambient Energy 42, 1447– 1455. https://doi.org/10.1080/01430750.2018.1563818
- Allbirds, 2022. We're changing so the climate doesn't [WWW Document]. URL https://www.allbirds.com/pages/our-commitment (accessed 4.13.22).
- Allcott, H., Mullainathan, S., Taubinsky, D., 2014. Energy policy with externalities and internalities. J. Public Econ. 112, 72–88. https://doi.org/10.1016/j.jpubeco.2014.01.004
- Álvarez Jaramillo, J., Zartha Sossa, J.W., Orozco Mendoza, G.L., 2018. Barriers to sustainability for small and medium enterprises in the framework of sustainable development. Bus. Strateg. Environ. 28, bse.2261. https://doi.org/10.1002/bse.2261
- Ambilkar, P., Dohale, V., Gunasekaran, A., Bilolikar, V., 2022. Product returns management: a comprehensive review and future research agenda. Int. J. Prod. Res. 60, 3920–3944. https://doi.org/10.1080/00207543.2021.1933645
- Ambilkar, P., Verma, P., Das, D., 2023. Sustailient supplier selection using neutrosophic best– worst approach: a case study of additively manufactured trinkets. Benchmarking An Int. J. https://doi.org/10.1108/BIJ-02-2023-0122
- Amer, M., Hamdy, M., Wortmann, T., Mustafa, A., Attia, S., 2020. Methodology for design decision support of cost-optimal zero-energy lightweight construction. Energy Build. 223,

110170. https://doi.org/10.1016/j.enbuild.2020.110170

- Aruta, G., Ascione, F., Bianco, N., Mastellone, M., 2022. Optimization of Envelopes , Systems and Storage for Transition of Building Stocks to Zero Energy Districts. Chem. Eng. Trans. 94, 841–846. https://doi.org/10.3303/CET2294140
- Aswathi Mohan, A., Robert Antony, A., Greeshma, K., Yun, J.H., Ramanan, R., Kim, H.S., 2022. Algal biopolymers as sustainable resources for a net-zero carbon bioeconomy. Bioresour. Technol. 344, 126397. https://doi.org/10.1016/j.biortech.2021.126397
- Ayyildiz, E., Taskin Gumus, A., 2021. A novel distance learning ergonomics checklist and risk evaluation methodology: A case of Covid‐19 pandemic. Hum. Factors Ergon. Manuf. Serv. Ind. 31, 397–411. https://doi.org/10.1002/hfm.20908
- Bai, C., Zhu, Q., Sarkis, J., 2022. Supplier portfolio selection and order allocation under carbon neutrality: Introducing a "Cool"ing model. Comput. Ind. Eng. 170, 108335. https://doi.org/10.1016/j.cie.2022.108335
- Balcombe, P., Brierley, J., Lewis, C., Skatvedt, L., Speirs, J., Hawkes, A., Staffell, I., 2019. How to decarbonise international shipping: Options for fuels, technologies and policies. Energy Convers. Manag. 182, 72–88. https://doi.org/10.1016/j.enconman.2018.12.080
- Belhadi, A., Kamble, S., Fosso Wamba, S., Queiroz, M.M., 2022. Building supply-chain resilience: an artificial intelligence-based technique and decision-making framework. Int. J. Prod. Res. 60, 4487–4507. https://doi.org/10.1080/00207543.2021.1950935
- Bokrantz, J., Skoogh, A., Berlin, C., Stahre, J., 2017. Maintenance in digitalised manufacturing : Delphi-based scenarios for 2030. Int. J. Prod. Econ. 191, 154–169. https://doi.org/10.1016/j.ijpe.2017.06.010
- Buchanan, D.A., McCalman, J., 1989. High Performance Work Systems: The Digital Experience. Rouderedge, London.
- Castaldo, V.L., Pisello, A.L., Piselli, C., Fabiani, C., Cotana, F., Santamouris, M., 2018. How outdoor microclimate mitigation affects building thermal-energy performance: A new designstage method for energy saving in residential near-zero energy settlements in Italy. Renew. Energy 127, 920–935. https://doi.org/10.1016/j.renene.2018.04.090
- Castillo, E., Gutiérrez, J.M., Hadi, A.S., 1997. Expert Systems and Probabilistic Network Models, Monographs in Computer Science. Springer New York, New York, NY. https://doi.org/10.1007/978-1-4612-2270-5
- Chen, J., Gao, M., Mangla, S.K., Song, M., Wen, J., 2020. Effects of technological changes on China's carbon emissions. Technol. Forecast. Soc. Change 153, 119938. https://doi.org/10.1016/j.techfore.2020.119938
- Chen, L., Msigwa, G., Yang, M., Osman, A.I., Fawzy, S., Rooney, D.W., Yap, P.-S., 2022. Strategies to achieve a carbon neutral society: a review. Environ. Chem. Lett. 20, 2277–2310. https://doi.org/10.1007/s10311-022-01435-8
- Chen, X., Jang, E., 2022. A Sustainable Supply Chain Network Model Considering Carbon Neutrality and Personalization. Sustainability 14, 4803. https://doi.org/10.3390/su14084803
- COP26, 2021. The Glasgow climate pact. UN Climate Change Conference UK 2021, Glasgow, UK., in: Cop26: The Glasgow Climate Pact.
- Danone, 2021. Towards Carbon Neutrality [WWW Document]. URL https://www.danone.com/impact/planet/towards-carbon-neutrality.html (accessed 5.13.22).
- Davis, S.J., Lewis, N.S., Shaner, M., Aggarwal, S., Arent, D., Azevedo, I.L., Benson, S.M., Bradley, T., Brouwer, J., Chiang, Y.-M., Clack, C.T.M., Cohen, A., Doig, S., Edmonds, J., Fennell, P., Field, C.B., Hannegan, B., Hodge, B.-M., Hoffert, M.I., Ingersoll, E., Jaramillo, P., Lackner, K.S., Mach, K.J., Mastrandrea, M., Ogden, J., Peterson, P.F., Sanchez, D.L., Sperling, D., Stagner, J., Trancik, J.E., Yang, C.-J., Caldeira, K., 2018. Net-zero emissions energy systems. Science (80-. ). 360. https://doi.org/10.1126/science.aas9793
- de Sousa Jabbour, A.B.L., Chiappetta Jabbour, C.J., Sarkis, J., Gunasekaran, A., Furlan Matos Alves, M.W., Ribeiro, D.A., 2019. Decarbonisation of operations management – looking back, moving forward: a review and implications for the production research community. Int. J. Prod. Res. 57, 4743–4765. https://doi.org/10.1080/00207543.2017.1421790
- Dohale, V., Akarte, M., Gunasekaran, A., Verma, P., 2022a. Exploring the role of artificial intelligence in building production resilience: learnings from the COVID-19 pandemic. Int. J. Prod. Res. 1–17. https://doi.org/10.1080/00207543.2022.2127961
- Dohale, V., Akarte, M., Gupta, S., Verma, V., 2021a. Additive Manufacturing Process Selection Using MCDM, in: Kalamkar, V., Monkova, K. (Eds.), Advances in Mechanical Engineering, Lecture Notes in Mechanical Engineering. Springer, Singapore, pp. 601–609. https://doi.org/10.1007/978-981-15-3639-7\_72
- Dohale, V., Ambilkar, P., Bilolikar, V., Narkhede, B.E., Kumar, Ashwani, Kumar, Anil, 2023a. Evaluating circular economy and smart technology adoption barriers in the Indian textile and apparel industries using neutrosophic ISM. Ann. Oper. Res. https://doi.org/10.1007/s10479- 023-05651-5
- Dohale, V., Ambilkar, P., Gunasekaran, A., Bilolikar, V., 2022b. Examining the barriers to operationalization of humanitarian supply chains: lessons learned from COVID-19 crisis. Ann. Oper. Res. https://doi.org/10.1007/s10479-022-04752-x
- Dohale, V., Ambilkar, P., Kumar, A., Mangla, S.K., Bilolikar, V., 2023b. Analyzing the enablers of circular supply chain using Neutrosophic-ISM method: lessons from the Indian apparel industry. Int. J. Logist. Manag. 34, 611–643. https://doi.org/10.1108/IJLM-03-2022-0141
- Dohale, V., Gunasekaran, A., Akarte, M., Verma, P., 2021b. An integrated Delphi-MCDM-Bayesian Network framework for production system selection. Int. J. Prod. Econ. 242, 108296. https://doi.org/10.1016/j.ijpe.2021.108296
- Dohale, V., Verma, P., Gunasekaran, A., Ambilkar, P., 2023c. COVID-19 and supply chain risk mitigation: a case study from India. Int. J. Logist. Manag. 34, 417–442. https://doi.org/10.1108/IJLM-04-2021-0197
- Du, H., Zhang, H., 2022. Climate neutrality in the EU and China: An analysis of the stringency of targets and the adaptiveness of the relevant legal frameworks. Rev. Eur. Comp. Int. Environ. Law. https://doi.org/10.1111/reel.12453
- Dutta, G., Kumar, R., Sindhwani, R., Singh, R.K., 2021. Adopting Shop Floor Digitalization in Indian Manufacturing SMEs—A Transformational Study, in: Lecture Notes in Mechanical Engineering. pp. 599–611. https://doi.org/10.1007/978-981-33-4320-7\_53
- Ellen MacArthur Foundation, 2016. Circular economy in India: Rethinking Growth for Lon-Term Prosperity.
- Elshkaki, A., Shen, L., 2022. Energy Transition towards Carbon Neutrality. Energies 15, 4967. https://doi.org/10.3390/en15144967
- Ford, R., Maidment, C., Vigurs, C., Fell, M.J., Morris, M., 2021. Smart local energy systems (SLES): A framework for exploring transition, context, and impacts. Technol. Forecast. Soc. Change 166, 120612. https://doi.org/10.1016/j.techfore.2021.120612
- Forgie, J., Carlson, A., 2018. Overcoming Organizational Barriers to Carbon Neutrality: Lessons from the UC Experience. POLICY Br. 9, 1–11.
- GeNIe, 2022. GeNIe Modeler USER MANUAL [WWW Document]. URL https://support.bayesfusion.com/docs/GeNIe.pdf
- Ghadge, A., Wurtmann, H., Seuring, S., 2020. Managing climate change risks in global supply chains: a review and research agenda. Int. J. Prod. Res. 58, 44–64. https://doi.org/10.1080/00207543.2019.1629670
- Ghobakhloo, M., Iranmanesh, M., Mubarak, M.F., Mubarik, M., Rejeb, A., Nilashi, M., 2022. Identifying industry 5.0 contributions to sustainable development: A strategy roadmap for delivering sustainability values. Sustain. Prod. Consum. 33, 716–737. https://doi.org/10.1016/j.spc.2022.08.003
- Ghuge, S., Dohale, V., Akarte, M., 2022. Spare part segmentation for additive manufacturing A framework. Comput. Ind. Eng. 169, 108277. https://doi.org/10.1016/j.cie.2022.108277
- Gong, Y., Jia, F., Brown, S., Koh, L., 2018. Supply chain learning of sustainability in multi-tier supply chains. Int. J. Oper. Prod. Manag. 38, 1061–1090. https://doi.org/10.1108/IJOPM-05- 2017-0306
- Govindan, K., Muduli, K., Devika, K., Barve, A., 2016. Investigation of the influential strength of factors on adoption of green supply chain management practices: An Indian mining scenario. Resour. Conserv. Recycl. 107, 185–194. https://doi.org/10.1016/j.resconrec.2015.05.022
- Hai, H.L., Liu, F.-H.F., 2007. Using the total vote-ranking to explore the pairwise comparison method for analytic hierarchy process. J. Stat. Manag. Syst. 10, 195–209. https://doi.org/10.1080/09720510.2007.10701248
- Hewlett Packard, 2022. Earth, we hear you [WWW Document]. URL https://www.hp.com/usen/hp-information/sustainable-impact/planet.html (accessed 5.25.22).
- Hobson, J., Hagan, A., 2019. How Allbirds Turned Wool Sneakers into A Billion-Dollar Business [WWW Document]. URL https://www.wbur.org/hereandnow/2019/09/10/allbirds-timbrown-wool-sneakers (accessed 4.14.22).
- Horowitz, C.A., 2016. Paris Agreement. Int. Leg. Mater. 55, 740–755.

https://doi.org/10.1017/S0020782900004253

- Hosseini, S., Barker, K., 2016a. A Bayesian network model for resilience-based supplier selection. Int. J. Prod. Econ. 180, 68–87. https://doi.org/10.1016/j.ijpe.2016.07.007
- Hosseini, S., Barker, K., 2016b. Modeling infrastructure resilience using Bayesian networks: A case study of inland waterway ports. Comput. Ind. Eng. 93, 252–266. https://doi.org/10.1016/j.cie.2016.01.007
- Hosseini, S., Ivanov, D., 2021. A multi-layer Bayesian network method for supply chain disruption modelling in the wake of the COVID-19 pandemic. Int. J. Prod. Res. https://doi.org/10.1080/00207543.2021.1953180
- Hosseini, S., Ivanov, D., Dolgui, A., 2020. Ripple effect modelling of supplier disruption: integrated Markov chain and dynamic Bayesian network approach. Int. J. Prod. Res. 58, 3284–3303. https://doi.org/10.1080/00207543.2019.1661538
- Hosseini, S., Sarder, M., 2019. Development of a Bayesian network model for optimal site selection of electric vehicle charging station. Electr. Power Energy Syst. 105, 110–122. https://doi.org/10.1016/j.ijepes.2018.08.011
- Hou, N., Zhu, Q., Zhao, W., Luo, Y., Liu, W., 2022. Study on the impact of green management of paper enterprises on carbon performance in the background of carbon peaking and carbon neutrality. Energy Reports 8, 10991–11002. https://doi.org/10.1016/j.egyr.2022.08.210
- Huang, Y., Yu, Q., Wang, R., 2021. Driving factors and decoupling effect of carbon footprint pressure in China: Based on net primary production. Technol. Forecast. Soc. Change 167, 120722. https://doi.org/10.1016/j.techfore.2021.120722
- Jain, R.K., Domen, J.K., 2016. Environmental Impact of Mining and Mineral Processing, Environmental Impact of Mining and Mineral Processing. Elsevier. https://doi.org/10.1016/C2014-0-05174-X
- Kahraman, C., Onar, S.C., Oztaysi, B., 2015. Fuzzy Multicriteria Decision-Making: A Literature Review. Int. J. Comput. Intell. Syst. 8, 637. https://doi.org/10.1080/18756891.2015.1046325
- Kamble, S.S., Gunasekaran, A., Kumar, V., Belhadi, A., Foropon, C., 2021. A machine learning based approach for predicting blockchain adoption in supply Chain. Technol. Forecast. Soc. Change 163, 120465. https://doi.org/10.1016/j.techfore.2020.120465
- Kang, J.-N., Wei, Y.-M., Liu, L., Wang, J.-W., 2021. Observing technology reserves of carbon capture and storage via patent data: Paving the way for carbon neutral. Technol. Forecast. Soc. Change 171, 120933. https://doi.org/10.1016/j.techfore.2021.120933
- Karuppiah, K., Sankaranarayanan, B., Ali, S.M., Chowdhury, P., Paul, S.K., 2020. An integrated approach to modeling the barriers in implementing green manufacturing practices in SMEs. J. Clean. Prod. 265, 121737. https://doi.org/10.1016/j.jclepro.2020.121737
- Kaya, R., Salhi, S., Spiegler, V., 2023. A novel integration of MCDM methods and Bayesian networks: the case of incomplete expert knowledge. Ann. Oper. Res. 320, 205–234. https://doi.org/10.1007/s10479-022-04996-7
- Kemp, R., Loorbach, D., Rotmans, J., 2007. Transition management as a model for managing processes of co-evolution towards sustainable development. Int. J. Sustain. Dev. World Ecol. 14, 78–91. https://doi.org/10.1080/13504500709469709
- Koirala, B.P., Koliou, E., Friege, J., Hakvoort, R.A., Herder, P.M., 2016. Energetic communities for community energy: A review of key issues and trends shaping integrated community energy systems. Renew. Sustain. Energy Rev. 56, 722–744. https://doi.org/10.1016/j.rser.2015.11.080
- Kumar, A., 2021. Transition management theory-based policy framework for analyzing environmentally responsible freight transport practices. J. Clean. Prod. 294, 126209. https://doi.org/10.1016/j.jclepro.2021.126209
- Kumar, R., Sindhwani, R., Singh, P.L., 2022. IIoT implementation challenges: analysis and mitigation by blockchain. J. Glob. Oper. Strateg. Sourc. 15, 363–379. https://doi.org/10.1108/JGOSS-08-2021-0056
- Laguna-Sánchez, P., Palomo, J., de la Fuente-Cabrero, C., de Castro-Pardo, M., 2020. A Multiple Criteria Decision Making Approach to Designing Teaching Plans in Higher Education Institutions. Mathematics 9, 9. https://doi.org/10.3390/math9010009
- Linton, S., Clarke, A., Tozer, L., 2022. Technical pathways to deep decarbonization in cities: Eight best practice case studies of transformational climate mitigation. Energy Res. Soc. Sci. 86, 102422. https://doi.org/10.1016/j.erss.2021.102422
- Liu, F.-H.F., Hai, H.L., 2005. The voting analytic hierarchy process method for selecting supplier. Int. J. Prod. Econ. 97, 308–317. https://doi.org/10.1016/j.ijpe.2004.09.005
- Liu, S., Li, H., Zhang, K., Lau, H.C., 2022. Techno-economic analysis of using carbon capture and storage (CCS) in decarbonizing China's coal-fired power plants. J. Clean. Prod. 351, 131384. https://doi.org/10.1016/j.jclepro.2022.131384
- Loorbach, D., 2010. Transition Management for Sustainable Development: A Prescriptive, Complexity-Based Governance Framework. Governance 23, 161–183. https://doi.org/10.1111/j.1468-0491.2009.01471.x
- Mahammedi, C., Mahdjoubi, L., Booth, C.A., Butt, T.E., 2022. Framework for preliminary risk assessment of brownfield sites. Sci. Total Environ. 807, 151069. https://doi.org/10.1016/j.scitotenv.2021.151069
- Mahapatra, S.K., Schoenherr, T., Jayaram, J., 2021. An assessment of factors contributing to firms' carbon footprint reduction efforts. Int. J. Prod. Econ. 235, 108073. https://doi.org/10.1016/j.ijpe.2021.108073
- Majumdar, A., Sinha, S., 2018. Modeling the barriers of green supply chain management in small and medium enterprises. Manag. Environ. Qual. An Int. J. 29, 1110–1122. https://doi.org/10.1108/MEQ-12-2017-0176
- Majumdar, A., Sinha, S.K., 2019. Analyzing the barriers of green textile supply chain management in Southeast Asia using interpretive structural modeling. Sustain. Prod. Consum. 17, 176– 187. https://doi.org/10.1016/j.spc.2018.10.005
- Majumdar, A., Sinha, S.K., Shaw, M., Mathiyazhagan, K., 2021. Analysing the vulnerability of green clothing supply chains in South and Southeast Asia using fuzzy analytic hierarchy process. Int. J. Prod. Res. 59, 752–771. https://doi.org/10.1080/00207543.2019.1708988
- Malhotra, M.K., Grover, V., 1998. An assessment of survey research in POM: from constructs to theory. J. Oper. Manag. 16, 407–425. https://doi.org/10.1016/S0272-6963(98)00021-7
- Mardani, A., Jusoh, A., Nor, K., Khalifah, Z., Valipour, A., 2015. Multiple criteria decisionmaking techniques and their applications – a review of the literature from 2000 to 2014. Econ. Res. Istraživanja 28, 516–571. https://doi.org/10.1080/1331677X.2015.1075139
- Martin, R., Muûls, M., de Preux, L.B., Wagner, U.J., 2012. Anatomy of a paradox: Management practices, organizational structure and energy efficiency. J. Environ. Econ. Manage. 63, 208– 223. https://doi.org/10.1016/j.jeem.2011.08.003
- Muthu, S.S., 2019. Circular Economy in Textiles and Apparel, Circular Economy in Textiles and Apparel: Processing, Manufacturing, and Design. Elsevier. https://doi.org/10.1016/C2017-0- 03221-4
- Muthu, S.S., 2017. Textiles and Clothing Sustainability, Textile Science and Clothing Technology. Springer Singapore, Singapore. https://doi.org/10.1007/978-981-10-2131-2
- Noguchi, H., Ogawa, M., Ishii, H., 2002. The appropriate total ranking method using DEA for multiple categorized purposes. J. Comput. Appl. Math. 146, 155–166. https://doi.org/10.1016/S0377-0427(02)00425-9
- O'Rourke, D., Strand, R., 2017. Patagonia: Driving Sustainable Innovation by Embracing Tensions. Calif. Manage. Rev. 60, 102–125. https://doi.org/10.1177/0008125617727748
- Oelze, N., 2017. Sustainable Supply Chain Management Implementation–Enablers and Barriers in the Textile Industry. Sustainability 9, 1435. https://doi.org/10.3390/su9081435
- Okay, E., 2016. Towards Smart Cities in Turkey?, in: Smart Cities and Smart Spaces: Concepts, Methodologies, Tools, and Applications. IGI Global, pp. 277–302. https://doi.org/10.4018/978-1-4666-9723-2.ch015
- Osorio, A.M., Úsuga, L.F., Vásquez, R.E., Nieto-Londoño, C., Rinaudo, M.E., Martínez, J.A., Leal Filho, W., 2022. Towards Carbon Neutrality in Higher Education Institutions: Case of Two Private Universities in Colombia. Sustainability 14, 1774. https://doi.org/10.3390/su14031774
- Park, B.R., Chung, M.H., 2022. An Analysis of the Energy-Saving Potential of Residential Buildings after the Introduction of Mandatory Zero-Energy Buildings to Achieve Carbon Neutrality in Korea. SSRN Electron. J. 1–28. https://doi.org/10.2139/ssrn.4168643
- Pishchulov, G., Trautrims, A., Chesney, T., Gold, S., Schwab, L., 2019. The Voting Analytic Hierarchy Process revisited: A revised method with application to sustainable supplier selection. Int. J. Prod. Econ. 211, 166–179. https://doi.org/10.1016/j.ijpe.2019.01.025
- Plambeck, E.L., 2012. Reducing greenhouse gas emissions through operations and supply chain management. Energy Econ. 34, S64–S74. https://doi.org/10.1016/j.eneco.2012.08.031
- Ran, F., Yang, X., Xu, X., Li, S., Liu, Y., Shao, L., 2021. Green activation of sustainable resources to synthesize nitrogen-doped oxygen-riched porous carbon nanosheets towards highperformance supercapacitor. Chem. Eng. J. 412, 128673. https://doi.org/10.1016/j.cej.2021.128673
- Rayer, Q., Jenkins, S., Walton, P., 2022. Defining Net-Zero and Climate Recommendations for Carbon Offsetting, in: Business and Policy Solutions to Climate Change. pp. 13–35. https://doi.org/10.1007/978-3-030-86803-1\_2
- Rootzén, J., Karlsson, I., Johnsson, F., Kadefors, A., Uppenberg, S., 2020. Supply-chain collective action towards zero CO 2 emissions in infrastructure construction: mapping barriers and opportunities. IOP Conf. Ser. Earth Environ. Sci. 588, 042064. https://doi.org/10.1088/1755- 1315/588/4/042064
- Rotmans, J., Kemp, R., van Asselt, M., 2001. More evolution than revolution: transition management in public policy. Foresight 3, 15–31. https://doi.org/10.1108/14636680110803003
- Sarasini, S., Linder, M., 2018. Integrating a business model perspective into transition theory: The example of new mobility services. Environ. Innov. Soc. Transitions 27, 16–31. https://doi.org/10.1016/j.eist.2017.09.004
- Shankar, R., Pathak, D.K., Choudhary, D., 2019. Decarbonizing freight transportation: An integrated EFA-TISM approach to model enablers of dedicated freight corridors. Technol. Forecast. Soc. Change 143, 85–100. https://doi.org/10.1016/j.techfore.2019.03.010
- Sharma, G., Rai, R.N., 2020. Modeling and analysis of factors affecting repair effectiveness of repairable systems using Bayesian network. Appl. Soft Comput. J. 92, 106261. https://doi.org/10.1016/j.asoc.2020.106261
- Shukla, T., 2020. Where does textile waste go? [WWW Document]. Circ. Appar. Innov. Fact. URL https://circularapparel.co/blog/2020/07/13/where-does-textile-waste-go/ (accessed 3.25.20).
- Sindhwani, R., Kumar, R., Behl, A., Singh, P.L., Kumar, A., Gupta, T., 2022a. Modelling enablers of efficiency and sustainability of healthcare: a m-TISM approach. Benchmarking An Int. J. 29, 767–792. https://doi.org/10.1108/BIJ-03-2021-0132
- Sindhwani, R., Singh, P.L., Behl, A., Afridi, M.S., Sammanit, D., Tiwari, A.K., 2022b. Modeling the critical success factors of implementing net zero emission (NZE) and promoting resilience and social value creation. Technol. Forecast. Soc. Change 181, 121759. https://doi.org/10.1016/j.techfore.2022.121759
- Soltanifar, M., Hosseinzadeh Lotfi, F., 2011. The voting analytic hierarchy process method for discriminating among efficient decision making units in data envelopment analysis. Comput. Ind. Eng. 60, 585–592. https://doi.org/10.1016/j.cie.2010.12.016
- Song, M., Wang, S., Zhang, H., 2020. Could environmental regulation and R& D tax incentives affect green product innovation? J. Clean. Prod. 258, 120849. https://doi.org/10.1016/j.jclepro.2020.120849
- Sudarsan, J.S., Vaishampayan, S., Parija, P., 2022. Making a case for sustainable building

materials to promote carbon neutrality in Indian scenario. Clean Technol. Environ. Policy 24, 1609–1617. https://doi.org/10.1007/s10098-021-02251-4

- Tumpa, T.J., Ali, S.M., Rahman, M.H., Paul, S.K., Chowdhury, P., Rehman Khan, S.A., 2019. Barriers to green supply chain management: An emerging economy context. J. Clean. Prod. 236, 117617. https://doi.org/10.1016/j.jclepro.2019.117617
- UN, 2020. Take Action for the Sustainable Development Goals [WWW Document]. Sustain. Dev. Goals. URL https://www.un.org/sustainabledevelopment/sustainable-development-goals/ (accessed 12.21.23).
- UN, 2015. THE 17 GOALS Sustainable Development Goals [WWW Document]. URL https://sdgs.un.org/goals (accessed 4.13.22).
- van Sluisveld, M.A.E., Hof, A.F., van Vuuren, D.P., Boot, P., Criqui, P., Matthes, F.C., Notenboom, J., Pedersen, S.L., Pfluger, B., Watson, J., 2017. Low-carbon strategies towards 2050: Comparing ex-ante policy evaluation studies and national planning processes in Europe. Environ. Sci. Policy 78, 89–96. https://doi.org/10.1016/j.envsci.2017.08.022
- VOGUE, 2021. Fashion is chasing carbon neutrality. Carbon positive is better [WWW Document]. URL https://www.voguebusiness.com/sustainability/fashion-is-chasing-carbon-neutralitycarbon-positive-is-better-allbirds-reformation-nicholas-kirkwood
- Waisman, H., Bataille, C., Winkler, H., Jotzo, F., Shukla, P., Colombier, M., Buira, D., Criqui, P., Fischedick, M., Kainuma, M., La Rovere, E., Pye, S., Safonov, G., Siagian, U., Teng, F., Virdis, M.-R., Williams, J., Young, S., Anandarajah, G., Boer, R., Cho, Y., Denis-Ryan, A., Dhar, S., Gaeta, M., Gesteira, C., Haley, B., Hourcade, J.-C., Liu, Q., Lugovoy, O., Masui, T., Mathy, S., Oshiro, K., Parrado, R., Pathak, M., Potashnikov, V., Samadi, S., Sawyer, D., Spencer, T., Tovilla, J., Trollip, H., 2019. A pathway design framework for national low greenhouse gas emission development strategies. Nat. Clim. Chang. 9, 261–268. https://doi.org/10.1038/s41558-019-0442-8
- Walmart, 2017. Walmart Launches Project Gigaton to Reduce Emissions in Company's Supply Chain **IWWW** Document I. URL https://corporate.walmart.com/newsroom/2017/04/19/walmart-launches-project-gigaton-toreduce-emissions-in-companys-supply-chain (accessed 5.25.22).
- Wang, J., Zhao, C., 2022. Reducing carbon footprint in a resilient supply chain: examining the critical influencing factors of process integration. Int. J. Prod. Res. https://doi.org/10.1080/00207543.2022.2063088
- Wannags, L.L., Gold, S., 2022. The Quest for Low-Carbon Mobility: Sustainability Tensions and Responses When Retail Translates a Manufacturer's Decarbonization Strategy. Organ. Environ. 35, 202–232. https://doi.org/10.1177/10860266211028645
- Wu, X., Tian, Z., Guo, J., 2022. A review of the theoretical research and practical progress of carbon neutrality. Sustain. Oper. Comput. 3, 54–66. https://doi.org/10.1016/j.susoc.2021.10.001
- Wuest, T., Weimer, D., Irgens, C., Thoben, K., Wuest, T., Weimer, D., Irgens, C., Thoben, K., 2016. Machine learning in manufacturing : advantages, challenges, and applications. Prod.

Manuf. Res. 4, 23–45. https://doi.org/10.1080/21693277.2016.1192517

Zhang, A., Tay, H.L., Alvi, M.F., Wang, J.X., Gong, Y., 2022. Carbon neutrality drivers and implications for firm performance and supply chain management. Bus. Strateg. Environ. https://doi.org/10.1002/bse.3230

<b>Particulars</b>	<b>Content</b>	<b>No. of Experts</b>	$\frac{0}{0}$		
Academic	Ph.D.	11	8.80%		
Qualification	Post-Graduate	98	78.40%		
	Graduate	16	12.80%		
	Director	3	2.40%		
Designation	<b>Top Level Manager</b>	67	53.60%		
	<b>Senior Level Managers</b>	31	24.80%		
	Junior Level Managers	24	19.20%		
	$26-30+Years$	13	10.40%		
	$21-25$ Years	34	27.20%		
Work Experience	$16-20$ Years	32	25.60%		
	$11-15$ Years	27	21.60%		
	$05-10$ Years	19	15.20%		

**Appendix I**. Profile of Respondents for validatory survey, VAHP, and BN



# **Appendix II.** Data collection and assessment for validatory survey

(Note: The number in cell represent the number of respondents choosing a particular option)



**Appendix III**. Survey for collecting prior probability data for Bayesian Network (BN) model

(Note: The number in cell represents the number of experts choosing the particular response)