An Original Information Entropy-Based Quantitative Evaluation Model for Low-carbon Operations in an Emerging Market

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Highlights

• We model the information entropy of different low-carbon operations management practices
• Low carbon logistics, manufacturing processes and new product development are considered
• Information entropy is adopted to develop probabilistically distinctive weightings for low-carbon managerial practices, computed using alternative models.
• There is heterogeneity in the ways that different companies perceive the issue of low-carbon practices
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Abstract
Drawing on the mixed results provided by the existing literature on low-carbon operations management practices, this paper proposes an original evaluation model for CO₂ emission reduction practices in Brazil, based on the concept of information entropy. We model the information entropy of different low-carbon operations management practices, such as logistics, manufacturing processes and new product development. Then, in light of the role of stakeholder pressures, motivations and barriers, we take a novel approach to assessing the relative importance of elements of the model by using information entropy to develop probabilistically distinctive weightings for low-carbon managerial practices, computed using a variety of models. These models include (a) the Fuzzy Rasch model, which combines Item Response Theory (IRT) and fuzzy set theory; (b) the Fuzzy AHP (Analytic Hierarch Process) model; and (c) the crisp AHP model, based on eight different judgment scales concerning the relative evolution of each criterion/construct. Our results, both expected and unexpected, suggest that: (i) there is heterogeneity in the ways that different companies perceive the issue of low-carbon practices; (ii) while the firms studied are motivated to reduce CO₂ emissions and such reduction is required by various stakeholders, the reduction is implemented solely through low-carbon logistics. Unexpectedly, we find that companies are not adopting a full-range of low-carbon operations practices, which may damage their overall performance. Implications for end-users and policy makers are highlighted.

Keywords: operations management; sustainable operations; information entropy; low-carbon economy; emerging markets.

1. Introduction
As the debate around climate change and the role of companies in the transition towards a low-carbon economy intensifies, pragmatic information which can support end-users’ decision-making processes is still lacking (de Sousa Jabbour et al., 2018). For example, what are the main low-carbon operations management practices adopted
by companies in order to reduce their CO₂ emissions? What are the effects of barriers, motivations and stakeholders’ influence on the adoption of these practices? The available responses to such questions are not unanimous, resulting in a need for a clearer understanding of the current status of managerial practices used to mitigate CO₂ emission levels, in light of different motivations, barriers and pressures from stakeholders. This focus on low-carbon operations is justified by the fact that companies in general are responsible for significant environmental impacts (Damert et al., 2018) through their logistics, manufacturing processes and product development activities (de Sousa Jabbour et al., 2018; Böttcher and Müller, 2015).

Previous research into low-carbon management practices adopted by companies has provided mixed results, necessitating further work, such as this paper. For example, from a narrow point of view, companies can benefit from adopting low-carbon management practices (Hoffman, 2005; Herrmann and Guenther, 2017); however, such adoption tends to face challenges (Tsalis and Nikolaou, 2017). Companies tend to experience many difficulties when reducing emissions, which has led to erratic (Paul et al., 2017) and heterogeneous approaches to this issue (Penz and Polsa, 2018). Additionally, no consensus has been formed as to the effects of low-carbon practices on firms’ performance (Damert and Baumgartner 2018). Furthermore, it has been argued that pressure from stakeholders drives some organizational responses to climate change (Cadez et al. 2019; Damert et al. 2017). However, it has not been made clear whether such pressure from stakeholders generates barriers and/or motivations to the adoption of low-carbon operations management practices (Sovacool et al. 2018). Therefore, modeling a real situation in which to consider – within a single study – the constructs of barriers, motivations and stakeholders’ influence on the adoption of low-carbon operations management practices is important in order to advance understanding of the transition towards a low-carbon economy. In this work, barriers, motivations, and stakeholders’ influence are considered constructs, and thus they are as much as uncertain as some practices that are taken into action by firms responding to climate change. Additionally, by considering barriers, motivations and stakeholders’ influence, this work refines the available literature on how firms respond to the transition towards low carbon operations management.

At the macro-level, looking across continents, it is important to highlight that there is no coordinated approach between Latin America (CDP, 2015), Asia, North America and Europe when it comes to supporting companies to pursue low-carbon
practices (CDP, 2014). Research into the low-carbon management strategies adopted by firms has featured a variety of countries; however, most studies have been concentrated on Europe (Böttcher and Müller, 2015; Damert and Baumgartner 2018) and Asia (Dubey et al., 2016; Suk, 2018; Zhu et al., 2018; Penz and Polsa, 2018), while, for example, there has been a general lack of studies from South America (Fahimnia et al., 2015). Overall, evidence concerning stakeholder pressures, motivations and barriers to low-carbon practices in firms located in developing economies — particularly the BRICs countries — remains largely under-researched (Jeswani et al., 2008). With regard to the methodological approaches adopted in studies conducted in the field of low-carbon operations management, the majority of the existing research seems to be based on either qualitative (Penz and Polsa, 2018) or statistical approaches (Böttcher and Müller, 2015; Damert and Baumgartner 2018), while modeling approaches can be viewed as scarce.

Spurred on by the aforementioned research gaps and contradictory results in low-carbon operations management, this original study compares data from 91 manufacturing firms located in Brazil by means of different methods and fuzzy logic. This research manipulates the weightings assigned to a number of criteria (including aspects of low-carbon operations management, stakeholder pressures, barriers and motivations) in order to infer their degree of randomness/predictability, so that CO₂ mitigation practices can be discussed in terms of homogeneity among firms. Additionally, this paper also unveils how these different practices are connected to each other, in terms of weighting importance.

In this research, information entropy is the cornerstone method used to assess the randomness or predictability of each practice, based on weightings computed using alternative multi-criteria methods, such as IRT and both the fuzzy and crisp versions of AHP. Compared with other methods, information entropy provides the benefits of higher accuracy and superior objectivity, which can lead to a more comprehensive interpretation of the results. Most noteworthy is that information entropy is suitable for all decision-making processes that require weight determination. Therefore, information entropy is used here to determine the weightings of various constructs/criteria and to provide support for the IRT and AHP methods used.

The structure of this paper includes four further sections. A literature review is presented in Section 2, while methodology is presented in Section 3. Section 4 focuses on the analysis and discussion of results, and conclusions are elaborated in Section 5.
2. Literature Review

Low-carbon operations management deals with improvements in product design, management models, transformation processes and equipment with the goal of mitigating carbon emissions and energy consumption (Du et al., 2015). Low-carbon operations embrace the development of low-carbon products, production processes and logistics (Böttcher and Müller, 2015). The adoption of these three types of low-carbon operations management practice is strongly supported by stakeholders, such as regulators (Damert et al., 2018). The low-carbon operations practices considered in this research are inspired by the work of Böttcher and Müller (2015).

The practice of ‘product design’ is an important instrument for sustainable development (Tang and Zhou, 2012). Products that reduce carbon emissions utilize more energy-efficient design, which reduces environmental impact throughout the product’s life cycle (Lee, 2012; Wesseling et al., 2017). In this research, low-carbon products are defined according to Böttcher and Müller (2015), based on:

- Use of life-cycle assessment (carbon footprint)
- Use of renewable and/or recycled raw materials
- Reduction of carbon emissions in the utilization phase

‘Low-carbon manufacturing processes’ include the development of energy-efficient projects and processes, which replace existing energy sources with cleaner fuels. Other such processes include reducing direct greenhouse gas emissions and developing a carbon inventory (Tang and Zhou, 2012; Alves et al., 2017). For the purposes of this study, we understand low-carbon manufacturing processes as:

- Measurement of carbon emissions in production processes
- Use of energy/carbon efficient equipment
- Use of low-carbon/carbon-free energy sources

Finally, ‘low-carbon logistics’ mainly relates to modes of transport, one of the largest sources of atmospheric emissions due to the consumption of fossil fuels (Tang and Zhou, 2012; Haddadsisakht and Ryan, 2018). Logistics managers can reassess transport options in order to minimize their carbon footprint and maximize the use of shipping space (Guiffrida et al., 2011; Han et al., 2017). In this work, low-carbon logistics is understood to involve:
• Measurement of carbon emissions of transportation processes
• Consolidation of shipments to reduce carbon emissions
• Use of carbon-efficient technologies and modes of transportation

Barriers to adopting low-carbon operations management practices involve, for example, a lack of either hard resources (equipment and assets) or soft resources (knowledge) (Amran et al., 2016; De Stefano, et al., 2016; Valero-Gil, et al., 2017). More significant barriers, especially those that might exist outside of stakeholder pressures, can seriously reduce the adoption of various carbon emissions reduction practices. Inspired by Liu (2014), the following barriers are considered in this research:

• Existence of a social and consumer context that does not encourage the reduction of CO₂ emissions by the company
• Existence of an internal organizational culture that does not encourage the reduction of CO₂ emissions
• Existence of a political and governmental context that does not encourage the reduction of CO₂ emissions
• Difficulty of including the topic of reducing CO₂ emissions in the workplace

At the same time, relevant motivators, including dedicating and building resources within organizations, can assist in the adoption of low-carbon practices (Leonidou et al., 2017). Cadez et al. (2019) find that market pressures for reducing greenhouse gas (GHG) emissions, perceived regulatory uncertainty related to GHG and level of focus on environmental strategy are important determinants of corporate GHG reduction strategies which, in turn, enhance GHG-related performance. Inspired by Böttcher and Müller (2015), the motivators we will consider are:

• Image improvement
• Marketing opportunities
• Cost reduction
• Differentiation from competitors

Companies tend to adopt low-carbon practices in response to increasing stakeholder pressures. For example, Penz and Polsa (2018) identify five areas of carbon footprint-related action – heating, building, travel, transportation and green services and products – and show that companies target actions in these areas towards different stakeholders in order to develop relationships with them. In this research, the following stakeholders are considered (Clarkson, 1995):
Customers  
Government  
Competitors  
Employees  
Suppliers  
Media

However, even when companies try to respond to stakeholder pressures, it is not always clear that the adoption of environmental practices results in improved performance. For example, the adoption of ISO 14001 certified environmental management systems and voluntary environmental practices do not always correlate to improvements in environmental performance (Darnall and Sides, 2008). There is also some ambiguity regarding the relationship between low-carbon operations and carbon performance (Damert et al., 2017). Few existing studies address the impact of carbon operations practices on the reduction of GHG emissions (Doda et al., 2016). An important aspect of evaluating these relationships is whether it is worthwhile for organizations to make significant investments in such efforts. It has also been posited that organizations may adopt certain practices as a ‘greenwashing’ effort, in order to improve their image, but that resulting benefits to environmental performance are not always apparent, since the focus may be on the signal to the marketplace (e.g. Wang and Sarkis, 2017). In terms of firms’ financial performance, Damert and Baumgartner (2018) do not find evidence for a relationship between financial performance and a company’s strategic approach to climate change.

Fresh empirical evidence from South Korea (Suk, 2018) and Germany (Böttcher and Müller, 2015) highlights the challenges of adopting low-carbon practices. According to Suk (2018), only a small proportion of Korean companies have advanced to the stage of proactive carbon management. For these companies, top managers’ support and understanding are, together with government pressure, essential factors for including carbon-related issues in their business strategies. This study provides implications for both policymaking and management through promoting carbon-oriented management via carbon policy (Suk, 2018). In Germany (Böttcher and Müller, 2015) it was found that stakeholder pressure – and, to some extent, expectations about competitiveness – drives the adoption of low-carbon operational practices. The relative and absolute effects of these drivers vary according to different practices. Regarding the
outcomes of these influences, positive effects on carbon performance and indirect effects on economic performance have been found. However, the results regarding both drivers and outcomes of the practices under consideration show significant differences with respect to firm size (Böttcher and Müller, 2015). In this study, it is expected that the adoption of low-carbon operations practices will lead to better performance in terms of (Böttcher and Müller, 2015):

- Energy use (per unit of output)
- Carbon emissions (per unit of output)
- Use of carbon-intensive materials (per unit of output)

With regard to the methodological approaches used by studies in the low-carbon operations management field, the majority of existing research seems to be based either on qualitative (Penz and Polsa, 2018) or statistical approaches (Böttcher and Müller, 2015; Damert and Baumgartner 2018), while modeling approaches are currently scarce.

The application of the information entropy methodology has been applied in order to weight criteria relating to the selection of suppliers based on environmental performance (dos Santos et al., 2019; Freeman and Chen, 2015), thus identifying the most critical enablers and barriers to the adoption of sustainability measures within the manufacturing domain (Bhanot et al., 2017) and evaluating indicators for the use of green technological innovations (Su et al., 2017). Therefore, this article pushes forward the debate concerning the application of modeling approaches, framing the challenges and solutions related to green issues and the transition to a low-carbon economy in the manufacturing domain.

3. Methodology

3.1 Research Sample and Data Collection Procedures

Brazil is the sample country chosen for this research. Brazil is especially suitable for this topic, as it is a developing economy and has proposed to reduce its greenhouse gas emissions by 37% by 2020 as part of the COP 21 agreement (Marcondes and Canto, 2015). This is a bold and risky target for a developing country, whose economy could be significantly affected by such an initiative. This agreement therefore shows that Brazil is committed to reducing carbon emissions, and industry will be central to meeting this goal. As Brazil is a huge country, logistics constitute a significant source of national CO₂ emissions, as does deforestation.
The criteria used to identify the sample companies for this study were: (a) those which manufacture mechanical capital goods, due to the potential environmental degradation caused by these processes and the fact that these companies may have to adapt their products and processes in order to comply with legal and stakeholder environmental requirements; and (b) those which are members of the Brazilian Machinery Builders’ Association (ABIMAQ) and the National Union of the Component Industry for Auto Parts (Sindipeças).

We sent email invitations to environmental managers or those holding similar positions within each company identified to participate in our research. The email contained a web link to access the online version of our questionnaire. We followed up with participants via telephone calls two weeks after the initial email. The survey was conducted over the course of 5 months, from the end of 2014 to mid-2015. The data collected was analyzed during 2016.

There were 882 companies in the original sample identified, and we received completed responses from 91 companies, giving a response rate of 10.32%. This sample size proved to be more than sufficient, taking into account a variety of parameters.

We conducted non-response bias testing by comparing respondents who returned the questionnaire early to those who returned it late. We used a t-test for this purpose, comparing the two groups by looking at the significance of Levene's test and equality of means. Our results show a significance value of > 0.05 for both sample groups regarding the variables tested, indicating that non-response bias is not a potential threat to our results.

The size characteristics of the companies which participated in the research are: 8 micro-sized, 20 small-sized, 38 medium-sized and 25 large-sized.

The questionnaire was designed by taking into account previously validated studies in this research field (Appendix A). We considered the most cited studies in each area, according to the Scopus database. Variables from Liu's 2014 article were used to describe barriers, while motivators of low-carbon operations management were based on scales used by Böttcher and Müller (2015). The constructs chosen to represent stakeholders include customers, government, competitors, employees, suppliers and media (Clarkson, 1995). We used a five-point Likert-scale to measure all items. The initial version of the questionnaire was validated through pre-testing with five academic experts in the sustainable operations field and two professional sustainability experts. A pilot study was conducted with operations management professionals. Based on
their feedback and results, it was decided that no changes to the survey instrument were required.

### 3.2 Selection of Methodology

Multiple Criteria Decision Making (MCDM) is a research field focused on the assessment of different alternatives when considering multiple criteria/constructs (Tsaur, Tzeng and Wang, 1997; Wang and Lee, 2009). The most common models applied to compute the weightings of these criteria/constructs include the Entropy Method (Tsaur, Tzeng and Wang, 1997; Singh and Benyoucef, 2011), Information Entropy Weight (IEW) (Zhang et al., 2011), Analytic Hierarchy Process (AHP) (Tsaur, Tzeng and Wang, 1997; Dagdeviren, Yavuz, and Kılınç, 2009; Yu, Guo, Guo and Huang, 2011), Fuzzy AHP (Wang, Cheng and Huang, 2009; Gumus, 2009; Sun, 2010) and Rough AHP (Aydogan, 2011).

Liang and Ding (2003) focus specifically on expert knowledge and experience to determine the weightings of criteria/constructs, based on perceptual Likert scales. However, the inherent uncertainty and subjectivity of such scales can result in weighting errors and problems in the weighting selection process. As a result, the criteria/construct weight selection process can yield varied results between experts. In response to this phenomenon, a growing body of research utilizes the association of fuzzy numbers with linguistic variables so that the vagueness of expert opinion on criteria/constructs can be adequately assessed. For example, Mahdavi et al. (2008) and Hsieh, Lu, and Tzeng (2004) use linguistic terms as conceptualized by Buckley (1985), varying from “very unimportant” to “very important”, to represent the fuzzy quantities generated. Kaufmann and Gupta (1991) and Mon, Cheng and Lin (1994) also use linguistic terms to express the fuzzy quantities given by experts. Although the linguistic terms conceptualized by Buckley (1985), Kaufmann and Gupta (1991) and Mon Cheng and Lin (1994) consider that various experts may assign the same fuzzy quantities to each criteria/construct, in fact there is still a level of uncertainty or vagueness among experts. Because of such uncertainty or vagueness among experts, this article focuses on bridging this gap by assessing the variance in weightings among different MCDM methods as an attempt to explore experts’ underlying preferences.

In this sense, Information Entropy (IE) can be conceptualized as a measure of uncertainty, which is a probabilistic concept. Depending on the relevant entropic characteristics, the randomness and dispersion produced by a random variable can be
determined by calculating the information entropy for each criterion under each sub-unit of analysis. The greater the information entropy value, the greater the randomness or dispersion within the range of respondents and, therefore, the greater the heterogeneity produced in analyzing this unknown phenomenon (Núñez et al., 1996). In this paper, information entropy is used to analyse the weighting distributions obtained by applying each one of the MCDM methods to the respondents’ preferences. Through this approach, a novel form of assessment is established, estimating the inherent heterogeneity of a given low-carbon operations criterion with respect to its epistemic uncertainty in achieving optimal managerial practices.

The following sub-sections present the different MCDM methods utilized in this article to explore experts’ underlying preferences.

3.2.1 Item Response Theory

Item Response Theory (IRT) is a discipline devoted to analyzing criteria/constructs and scale performance, as well as the relationships between scale performance and the criteria/constructs measured by the scale itself (Meads and Bentall, 2008). One method applied in this study is the Fuzzy Rasch model, which combines the Rasch model with fuzzy theory (Rasch, 1960). In essence, the Rasch model is applied to compute fuzzy weights for each expert consulted. Subsequently, an arithmetic averaging is performed. Finally, the ‘defuzzified’ weightings are obtained and can be used for comparability with other models, such as AHP and FAHP, as discussed in the following sections.

The Rating Scale Model (RSM) created by Andrich (1978) applies Rasch’s model to polytomous scales, such as the Likert scale. It considers that the probability of correctly measuring a criterion/construct in the scale is the result of a latent trait or ability (Kastrin and Peterlin, 2010). In this research, Eq. (1) is employed to assess the relevant respondent’s (or expert’s) preferences regarding each criterion/sub-criterion related to low-carbon managerial practices (as presented in Appendix B):

$$\log \left( \frac{P_{nij}}{P_{n(i-1)}} \right) = \theta_n + (\delta_i + \tau_j) \quad (1)$$

Where $P_{nij}$ and $P_{n(i-1)}$ represent the probability that the criterion/construct $n$ obtains scores $j$ and $j-1$ from expert $i$. $\theta_n$ represents the measure score of criterion/construct $n$, $\delta_i$ represents the measure score of expert $i$, and $\tau_j$ represents the step difficulty of score $j$. In this paper we followed the procedure presented in Wright
and Masters (1982), assuming that the step difficulty in the RSM is identical for all criteria/constructs, as is expected to be the case where Likert scales are used. Therefore, the joint effect between respondents’ preferences regarding each criterion/construct and its step difficulty can be assumed to be linear, as presented in Eq. (2) (Kim and Hong, 2004).

\[
\delta_{ij} = \delta_i + \tau_j \quad (2)
\]

In Eq. (2), \( i = 1, \ldots, E \), where \( E \) denotes the expert number. \( j = 1, \ldots, m \) with \( m \) representing the value of the linguistic score, which varies from “very unimportant” to “very important”.

**3.2.2 Analytic Hierarchy Process (AHP)**

AHP is a well-known MCDM created by Saaty (1977), which can help in improving judgments based on hierarchy, pair-wise comparisons, judgment scales, allocation of criteria/construct weights and selection of the best alternative from a finite number of variants through computation of different utility functions. Since its inception, there has been a vast amount of applications and developments related to this method.

Specifically, AHP uses a ratio scale, which is dimensionless, as opposed to measurements on an interval scale. Judgment in this process is based on the relative values of two criteria/constructs which share the same scale. The decision maker does not need to provide a numerical judgment; instead, a relative verbal appreciation is sufficient. The results of paired comparisons for \( n \) criteria/constructs are organized into positive reciprocal matrices (Saaty, 1977).

One of the most important characteristics of AHP is its evaluation of quantitative and qualitative criteria/constructs together on the same preference scale. These items can be numerical, verbal, or graphical. Although the use of verbal responses is intuitive, it may also allow for some ambiguity in non-trivial comparisons. In Saaty’s original version of AHP, verbal statements are represented by a scale measuring from one to nine. In this research, we departed from the linear verbal gradation, exploring several other numerical scales that have previously been proposed in the literature (see Table 1). These alternative numerical scales were included in this research for the sake of robustness and comparison of criteria/construct weightings within and between alternative models.
<table>
<thead>
<tr>
<th>Scale Type</th>
<th>Mathematical description</th>
<th>Parameters</th>
<th>Approximated scale values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear (Saaty, 1977)</td>
<td>S = x</td>
<td>x={1,2,...,5}</td>
<td>1;2;3;4;5</td>
</tr>
<tr>
<td>Power (Harker and Vargas, 1987)</td>
<td>S = x²</td>
<td>x={1,2,...,5}</td>
<td>1;4;9;16;25</td>
</tr>
<tr>
<td>Root Square (Harker and Vargas, 1987)</td>
<td>$S = \sqrt{2(x-1)}$</td>
<td>x={1,2,...,5}</td>
<td>1;\sqrt{2};\sqrt{3};2;\sqrt{5}</td>
</tr>
<tr>
<td>Geometric (Lootsma, 1989)</td>
<td>$S = \sqrt[3]{2x-1}$</td>
<td>x={1,2,...,5}</td>
<td>1;2;4;8;16</td>
</tr>
<tr>
<td>Inverse linear (Ma and Zheng, 1991)</td>
<td>$S = \frac{9}{10-x}$</td>
<td>x={1,2,...,5}</td>
<td>1;1.13;1.29;1.5;1.8</td>
</tr>
<tr>
<td>Asymptotical (Dodd and Donegan, 1995)</td>
<td>$S = \tanh^{-1}\left(\frac{\sqrt{3(x-1)}}{14}\right)$</td>
<td>x={1,2,...,5}</td>
<td>0;0.12;0.24;0.36;0.46</td>
</tr>
<tr>
<td>Balanced (Salo and Hämäläinen, 1997)</td>
<td>$S = \frac{w}{(1-w)}$</td>
<td>w={0.5, 0.55, 0.6,...,0.9}</td>
<td>1;1.22;1.5;1.86;2.33;4;5.67;9</td>
</tr>
<tr>
<td>Logarithmic (Ishizaka, Balkenborg and Kaplan, 2010)</td>
<td>$S = \log_2(x + 1)$</td>
<td>x={1,2,...,5}</td>
<td>1;1.58;2;2.32;2.58</td>
</tr>
</tbody>
</table>
3.2.3 Fuzzy AHP

Fuzzy AHP is an expansion of Saaty’s AHP method (1977), which was designed to handle vagueness in criteria/construct measurement (Lu et al., 2007; Shaverdi et al., 2011). Accordingly, the elements of the reciprocal matrices used in Fuzzy AHP are represented by fuzzy numbers instead of crisp ones (Chiou et al., 2005; Huang et al., 2008). Many papers have been published on both the theory and application of FAHP (Ahlaticoglu and Tiryaki, 2007; Stefanović et al., 2015). A comprehensive literature review of the relevant techniques can be found in Kahraman, Cebeci and Ruan (2004). Operational scales for FAHP can be found, for example, in Abdel-Kader and Dugdale (2001) and Wang and Chen (2007). These scales are used in this research due to their widespread acceptance. Table 2 presents the importance scale for each criterion/construct (Amiri, 2010).

In this paper, the FAHP computations used followed the following steps.

**Step 1:** Compute the relative importance of the criteria/constructs depicted in Appendix B. By means of a pairwise comparison, the matrix $\tilde{R}$, formed using fuzzy estimates for the relative respondent preferences, was built as follows:

$$\tilde{R} = \begin{bmatrix} C_1 & C_2 & \ldots & C_n \\ \tilde{r}_{11} & \tilde{r}_{12} & \ldots & \tilde{r}_{1n} \\ \tilde{r}_{21} & \tilde{r}_{22} & \ldots & \tilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{n1} & \tilde{r}_{n2} & \ldots & \tilde{r}_{nn} \end{bmatrix}$$

(App3)

Accordingly, pairwise comparison matrices for all criteria/constructs presented in Appendix B were developed based on the survey responses obtained in this research. Linguistic terms based on triangular fuzzy numbers (TFN) were assigned to these pairwise comparisons by considering the criterion preferences of each respondent, according to the linguistic scale depicted in Table 2, such as:

$$\tilde{R} = \begin{bmatrix} 1 & \tilde{r}_{12} & \ldots & \tilde{r}_{1n} \\ \tilde{r}_{21} & 1 & \ldots & \tilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{r}_{n1} & \tilde{r}_{n2} & \ldots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{r}_{12} & \ldots & \tilde{r}_{1n} \\ \frac{1}{\tilde{r}_{21}} & 1 & \ldots & \tilde{r}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{\tilde{r}_{n1}} & \frac{1}{\tilde{r}_{n2}} & \ldots & 1 \end{bmatrix}$$

(App4)

**Step 2:** Calculate fuzzy estimates for the weightings of the criteria/constructs based on the matrix $\tilde{R}$, squaring the triangular fuzzy matrices (TFM) repeatedly until convergence of the weightings is reached.
Step 3: Make pairwise comparisons of alternatives under each criterion/construct individually. Thus, $n$ matrices $(R^1, R^2, \ldots, R^n)$, each of which contains fuzzy estimates for the relative significance of each pair of criteria/constructs, were created.

$$R^i = \begin{bmatrix}
    A_1 & \tilde{r}_{11}^i & \tilde{r}_{12}^i & \cdots & \tilde{r}_{1m}^i \\
    \vdots & \tilde{r}_{21}^i & \tilde{r}_{22}^i & \cdots & \tilde{r}_{2m}^i \\
    \vdots & \vdots & \vdots & \ddots & \vdots \\
    A_m & \tilde{r}_{m1}^i & \tilde{r}_{m2}^i & \cdots & \tilde{r}_{mm}^i
\end{bmatrix}$$ (5)

Step 4: Calculate fuzzy estimates for the weighting of each alternative under each criterion separately, based on the matrices $(\tilde{R}^1, \tilde{R}^2, \ldots, \tilde{R}^n)$. More precisely, compute the fuzzy weights of each criterion/construct by multiplying the triangular fuzzy matrices, squaring the TFM several times using Buckley’s (1985) normalization at each iteration, which is described as follows:

$$\tilde{r} = (\tilde{a}_{j_1} \otimes \tilde{a}_{j_2} \otimes \cdots \otimes \tilde{a}_{in})^{1/n}$$ (6)

$$\tilde{w}_i = (\tilde{r}_1 \otimes \cdots \otimes \tilde{r}_n)^{-1}$$ (7)

where $\tilde{a}_{in}$ is a fuzzy comparison value of criterion $i$ to criterion $n$; thus, $\tilde{r}_i$ is the geometric mean of the fuzzy comparison value of criterion $i$ to each criterion. $\tilde{w}_i$ is the fuzzy weight of the $i^{th}$ criterion, which can be indicated by a Triangular Fuzzy Number, $\tilde{w}_i = (L_{w_i}, M_{w_i}, U_{w_i})$. Here, $L_{w_i}$, $M_{w_i}$ and $U_{w_i}$ stand for the lower, middle, and upper values of the fuzzy weight of the $i^{th}$ criterion/construct depicted in Appendix B. In this paper, these three values converged on the same crisp number resulting from the convergence of the power sequence of Triangular Fuzzy Matrices for a large number of iterations, in accordance with previous discussions on the topic in Thomason (1977), Hashimoto (1983), Kandel (1996) and Kolodziejczyk (1988). With respect to this result, this research differs from previous studies insofar as an exact solution is found for each criterion weight.

Step 5: Obtain a final score for each alternative by adding the weightings for each alternative (obtained in Step 4) multiplied by the weightings of the corresponding criteria (obtained in Step 2).

<table>
<thead>
<tr>
<th>Intensity of importance of each criterion</th>
<th>Linguistic preference scale in pairwise comparison</th>
<th>TFN scale</th>
<th>Reciprocal TFN scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>(1, 1, 1)</td>
<td>(1, 1, 1)</td>
</tr>
<tr>
<td>2</td>
<td>Intermediate values</td>
<td>(1/2, 3/4, 1)</td>
<td>(1, 4/3, 2)</td>
</tr>
</tbody>
</table>

Table 2. Detail of linguistic scale used for pairwise comparison
<table>
<thead>
<tr>
<th>TFN (triangular fuzzy numbers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>3 Moderate importance (2/3, 1, 3/2)</td>
</tr>
<tr>
<td>4 Intermediate values (1, 3/2, 2)</td>
</tr>
<tr>
<td>5 Strong importance (3/2, 2, 5/2)</td>
</tr>
<tr>
<td>6 Intermediate values (2, 5/2, 3)</td>
</tr>
<tr>
<td>7 Very high importance (5/2, 3, 7/2)</td>
</tr>
<tr>
<td>8 Intermediate values (2, 5/2, 3)</td>
</tr>
<tr>
<td>9 Extremely high importance (7/2, 4, 9/2)</td>
</tr>
</tbody>
</table>

3.2.4 Information Entropy

Information entropy as a measure of uncertainty is a probabilistic concept. According to the characteristics of entropy, the randomness and dispersion of a criterion/construct can be determined by calculating its information entropy. The greater the value of the information entropy, the greater the randomness or dispersion of the criterion/construct (Nunez et al. 1996).

In this paper, information entropy is used to analyze the distribution of criteria weightings obtained through IRT, AHP and Fuzzy AHP, through which process a novel assessment is established to estimate the homogeneity of experts’ evaluation among managerial practices, motivations, barriers and distinct stakeholders. The process of calculating information entropy involves a number of concepts, based on consideration of the following steps:

Step 1. It is assumed that there are $n$ criteria/constructs $X_1, X_2, X_3 \cdots X_n$ (as depicted in Appendix B) related to a given respondent preference $m$, the values of which make up the decision-making matrix $D$ as follows:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \quad (8)$$

Step 2. First, in order to ascertain the weighting of each criterion/construct, it is necessary to transform decision-making matrix $D$ into decision-making matrix $R$ via normalization:

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \quad (9)$$

In this matrix, the sum of each column element (or criterion/construct) equals 1; in other words, decision-making matrix $R$ satisfies Eq. (10), which captures the
information reliability level based on the respondents’ preferences for the given criterion/construct:

\[ \sum_{i=1}^{m} r_{ij} = 1, j = 1,2,3 \ldots, n (10) \]

**Step 3.** The column vectors \((A_1, A_2 \ldots A_n)\) of normalized decision-making matrix \(R\), namely the criteria/construct values \((r_{1j}, r_{2j} \ldots r_{mj})\), are treated as a probabilistic distribution of information based on the respondents’ preferences as dealt with by each method. Therefore, the information entropy \(E_j\) of criterion/construct \(X_j\) is defined as:

\[ E_j = \frac{1}{\ln m} \sum_{i=1}^{m} r_{ij} \ln r_{ij}, j = 1,2,3 \ldots, n (11) \]

where \(0 \leq E_j \leq 1\), and 1 denotes maximal entropy (minimal information reliability).

The information entropy values for each construct/criterion depicted in Appendix B were computed based on the respondents’ preferences (weightings), as captured by the previously described models. Information entropy can reveal how reliable the available information on low-carbon operational practices is, as perceived by managers within the scope of current practices. Lower information entropy may denote that a given low-carbon operational practice is well-regarded throughout the industry, since its information reliability as perceived by managers (respondents) is high. Conversely, higher information entropy may suggest that a given practice is still in the embryonic phase throughout the industry, and its status as a “best practice” is not yet clear to the respondents.

After presenting an overview of the modeling approaches selected for application in this study, the results of the modeling are presented and discussed in the following section.

4. Analysis and Discussion of Results

4.1. Results

Density plots for the weightings computed under each model for the sub-criteria/constructs are depicted in Figure 1 and can be found in Appendix B. The respective weightings for each criterion/sub-criterion are also given in the appendix. While it is possible to affirm that the weightings are somewhat dispersed and that information entropy tends to be high, both fuzzy models (Fuzzy IRT and Fuzzy AHP) presented smaller dispersion when compared to the AHP models and their scale variants. This may reflect the fact that fuzzy models only capture scale vagueness as separate from random effects.
As regards the main criteria/constructs, Figure 2 reveals that information entropy is high (above 0.90) for each of them. This suggests that the weightings assigned to CO₂ emissions practices in Brazil, as well as to these practices’ interrelationships with stakeholders, barriers, and motivations are strongly dispersed, thus implying heterogeneity among companies regarding how they perceive these respective issues. The three criteria with the highest weightings are related, in order, to perceptions of how the company has been affected by different stakeholders in the process of reducing CO₂ emissions, to the main motivators for reducing CO₂ emissions, and to the practices adopted for low-carbon logistics.

On the other hand, the three criteria with the lowest weightings relate to efforts to reduce CO₂ emissions over the last three years, to the barriers to reducing these emissions, and to low-carbon manufacturing practices. These results suggest that while reducing CO₂ emissions in operations management practices has a good level of motivation and is triggered by different stakeholders, its implementation is so far largely limited to logistics operations, possibly due to lower complexity in this area when compared to manufacturing and product development operations. Therefore, this finding may help to explain the perception of little progress having been made over the last three years in terms of continuing to lower CO₂ emissions and overcoming the barriers to doing so.

Nevertheless, there appears to be a trade-off between information entropy and criterion weightings; that is, higher information entropy (lower information reliability) implies a lower preference weighting, and vice-versa. While two visual clusters in Fig. 2 can be perceived – one formed by criteria 5, 6, and 7; the other formed by criteria 1, 2, 3, and 4 – this trade-off still holds, regarding the size of the company or the industry type. This suggests that respondents are less certain when it comes to stakeholder motivations and the intrinsic technological barriers to designing and delivering low-carbon products. This may reflect the fact that product design in Brazil is relatively non-existent, since most capital goods are not produced internally to the country but are rather imported, which imposes a technological gap which Brazilian respondents (and therefore, managers and companies) must overcome if low-carbon products are to be designed. On the other hand, as long as managerial and low-carbon logistics processes are more familiar to Brazilian managers, there are still information entropy issues that should be taken into account. While Brazilian transportation networks are strongly dependent on pollutant road transportation, different taxation structures across several...
Brazilian states are making the choice of less pollutant modes of transport, such as rail, river, and sea, more attractive.

The results of our k-means cluster analysis may shed some light on this issue (Figure 3). Two clusters were found, presenting an optimal split solution to these observations. Cluster 1 is formed by sub-criteria 1-15, which include all preference weightings regarding stakeholders, barriers and motivations, and only one sub-criterion related to low-carbon products: life-cycle assessment. In turn, Cluster 2 is formed by sub-criteria 16-26, which include all preference weightings regarding low-carbon processes, low-carbon logistics and low-carbon performance, as well as two remaining sub-criteria related to low-carbon products: renewable/recycled materials and reduced carbon emissions in the utilization phase.

Building upon the previous paragraphs, it is interesting to note that these two clusters, determined on the grounds of information entropy and weightings, were split specifically on the criteria related to low-carbon products. Although at first sight this may appear to be related to the specific limitations of Brazil, this result also sheds some light in terms of the proper dissemination of life-cycle assessment practices throughout different companies and industries. In fact, differently from recycling or use of renewable sources, life-cycle assessment presents several conceptual challenges related to inventory, impact assessment, generic and evolving aspects, with respect to ‘allocation’, ‘uncertainty’, ‘biodiversity’, ‘littering’, ‘animal well-being’ or ‘positive impacts’ which are not covered as often in existing reference manuals.
Figure 1. Density plot for the sub criteria weights computed with each model.

Figure 2. Information entropy vs. weight importance scatterplot (Crit = Criterion)
4.2 Implications for Managers and Policy Decision-Makers

Regarding implications for managers and policy decision-makers, the most relevant finding of this study is the suggestion that while reducing CO₂ emissions appears to be a highly motivated process and one which is important to a variety of stakeholders, its implementation has so far been limited largely to logistics, possibly due to lower complexity in this area when compared to the adaptation of manufacturing and product development operations. This finding may help to explain the perception of little progress having been made over the last three years in terms of lowering CO₂ emitting practices and overcoming the barriers to doing so.

In this context, managers may be able to enhance firms’ performance in terms of adopting low-carbon operations management practices by focusing not only on logistics, but by embracing low-carbon manufacturing processes and product development. A more comprehensive perspective on adopting a wide range of low-carbon operations management practices could help companies achieve their targets in terms of CO₂ emissions.

However, a more holistic perspective on adopting low-carbon operations management should also be supported by policy makers. Our research results suggest...
that companies are struggling to move beyond low-carbon logistics. This may be damaging firms’ performance. If policy makers want to support the transition towards a low-carbon society, they will need to develop plans to enhance the knowledge and skills available to industry. This can be achieved through specific financial support for promoting low-carbon manufacturing processes and product development. As Böttcher and Müller (2015) suggest, firms may be struggling to adopt more low-carbon operations practices either because they don’t have enough financial resources, or because they don’t have the necessary knowledge and skills.

4.3 Implications for Theory

The main findings of this research have significant implications for the development of low-carbon management theory. These implications can be divided between expected implications – those which are aligned with previous research in the field – and unexpected implications, which emerge from non-mainstream research results.

Regarding the expected findings, our research suggests that there is significant heterogeneity regarding the way firms perceive the role of stakeholder pressures, barriers and motivations when pursuing reduction of CO₂ emissions. Similar findings were observed, for example, by Cadez et al. (2019) and Böttcher and Müller (2015), as these authors found that the adoption of low-carbon management practices has not been consistent across firms.

Another expected research finding is the allocation of higher weightings for companies’ perceptions of stakeholder pressures, motivators and low-carbon logistics. This may help to confirm arguments from the state-of-the-art literature that put stakeholders at the heart of any explanation regarding companies’ adoption of low-carbon management approaches (Böttcher and Müller, 2015; Seles et al., 2018).

We also suggest some unexpected findings, such as the low weightings of certain low-carbon operations practices, namely low-carbon manufacturing processes and low-carbon product development. It should be noted that, while a large proportion of the existing literature considers these two practices to be key for low-carbon firms (Böttcher and Müller, 2015; Seles et al., 2018), the organizations surveyed have not adopted these practices as extensively as expected. In general, managers should be able to perceive long-term benefits of investing in low-carbon operations management by means of low-carbon manufacturing processes due to improved energy efficiency of operations (Alves
et al., in press); however, this has not been the case among the organizations surveyed here. Thus, perhaps, the organizations surveyed here have pursued short-term benefits instead.

Less comprehensive adoption of low-carbon operations practices was also found by Böttcher and Müller (2015). These authors point out that this may be due to a lack of knowledge regarding the benefits of low-carbon management for firms’ overall performance (Böttcher and Müller, 2015). We also found that companies have not fully perceived low-carbon operations as an effective way to improve firms’ performance. This kind of misalignment between low-carbon practices and firms’ performance has previously been reported in the literature (Damert and Baumgartner 2018). Additionally, according to Doda et al. (2016), the ways in which firms target the reduction of CO₂ emissions may blur the perception of carbon performance; one reason for this is the fact that practices and processes are not directed towards this end. Thus, the fact that the organizations surveyed have experienced barriers to adopting low-carbon manufacturing processes may impact on their perception of the reduction of CO₂ emissions over the last three years.

Finally, from a research methodology point of view, this research contributes to the state-of-the-art literature by adopting an information entropy perspective to deal with the issue of low-carbon practices. So far, the majority of research in this field has approached this issue through either qualitative or statistical perspectives. We also add to the existing theory in terms of shedding light on a less studied and developing national context: Brazil. As previously mentioned, the existing literature is short on evidence from Latin American-based firms, as there has been a prevalence of evidence from Europe and Asia.

5. Conclusions

In this work, we present research results concerning the application of information entropy to develop an original evaluation model of low-carbon operations management practices in Brazil. This model also takes into account elements such as stakeholder pressures, motivators and barriers to low-carbon management.

The main findings of our research suggest that there has been heterogeneity in the way companies perceive the adoption of low-carbon operations management practices. Overall, companies tend to invest more in low-carbon logistics. In this
context, low-carbon manufacturing processes and products tend to be neglected. The relatively low adoption of low-carbon processes and products should be analyzed further in future research. Specifically, we offer two lines of potential explanation that may be explored in future investigations:

- Large countries such as Brazil generate a significant part of their CO₂ emissions from transport and logistics. Is this phenomenon a general characteristic of territorially vast nations?
- Managers appear not to have the necessary knowledge and skills to go beyond low-carbon logistics. In this context, the question that emerges is: are low-carbon product development and manufacturing processes more challenging to adopt than low-carbon logistics?

Finally, it should be acknowledged that this research has certain natural limitations. This study focuses on data from companies located in Brazil, so the characteristics of this national context should be taken into account when interpreting the research findings. This research also focuses on three low-carbon operations management practices in particular (manufacturing process, products, and logistics); this scope may be widened in future research.

**References**


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**Appendix A.** Constructs and Variables of this Research

<table>
<thead>
<tr>
<th>Construct</th>
<th>Indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
</tbody>
</table>
| Stakeholders (criterion 1) (Clarkson, 1995) | • Customers (sub-criterion 1)  
• Government (sub-criterion 2)  
• Competitors (sub-criterion 3)  
• Employees (sub-criterion 4)  
• Suppliers (sub-criterion 5)  
• Media (sub-criterion 6) |
| --- | --- |
| Barriers (criterion 2) (Liu, 2014) | • There is a social and consumer context that does not encourage the reduction of CO₂ emissions by the company (sub-criterion 7)  
• There is an internal organizational culture that does not encourage the reduction of CO₂ emissions where I work (sub-criterion 8)  
• There is a political and governmental context that does not encourage the reduction of CO₂ emissions where I work (sub-criterion 9)  
• It is difficult to include the topic of reducing CO₂ emissions where I work (sub-criterion 10) |
| Motivations (criterion 3) (Böttcher and Müller, 2015) | • Image improvement (sub-criterion 11)  
• Marketing opportunities (sub-criterion 12)  
• Cost reduction (sub-criterion 13)  
• Differentiation from competitors (sub-criterion 14) |
| Low-carbon products (criterion 4) (Böttcher and Müller, 2015) | • Use of life cycle assessment (carbon footprint) (sub-criterion 15)  
• Use of renewable and/or recycled raw materials (sub-criterion 16)  
• Reduction of carbon emissions in utilization phase (sub-criterion 17) |
| Low-carbon processes (criterion 5) (Böttcher and Müller, 2015) | • Measurement of carbon emissions in production processes (sub-criterion 18)  
• Use of energy/carbon efficient equipment (sub-criterion 19)  
• Use of low-carbon/carbon-free energy sources (sub-criterion 20) |
| Low-carbon logistics (criterion 6) (Böttcher and Müller, 2015) | • Measurement of carbon emissions from transportation processes (sub-criterion 21)  
• Consolidation of shipments to reduce carbon emissions (sub-criterion 22)  
• Use of carbon-efficient technologies and modes of transportation (sub-criterion 23) |
| Carbon performance (criterion 7) (Böttcher and Müller, 2015) | • Energy use (per unit of output) (sub-criterion 24)  
• Carbon emissions (per unit of output) (sub-criterion 25)  
• Use of carbon-intensive materials (per unit of output) (sub-criterion 26) |
Appendix B. Weights Computed for Each Model and Each Criterion/Construct Including Respective Entropy (sc = subcriterion)

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Sub criteria</th>
<th>Final Weights</th>
<th>Criterion Information Entropy</th>
<th>Sub criteria informatio n Entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stakeholder pressures - Criterion 1</td>
<td>Customers (sc1)</td>
<td>Fuzzy IRT 0.0355  Fuzzy AHP 0.0346  AHP Linear 0.0777  AHP Power 0.1190  AHP Root Square 0.0570  AHP Geometric 0.0824  AHP Inverse Linear 0.0479  AHP Asymptotical 0.0018  AHP Balanced 0.0517  AHP Logarithmic 0.0624</td>
<td>0.9451</td>
<td>0.9284</td>
</tr>
<tr>
<td></td>
<td>Government (sc2)</td>
<td>Fuzzy IRT 0.0390  Fuzzy AHP 0.0373  AHP Linear 0.0694  AHP Power 0.0975  AHP Root Square 0.0538  AHP Geometric 0.0729  AHP Inverse Linear 0.0461  AHP Asymptotical 0.0020  AHP Balanced 0.0489  AHP Logarithmic 0.0581</td>
<td></td>
<td>0.9417</td>
</tr>
<tr>
<td></td>
<td>Competitors (sc3)</td>
<td>Fuzzy IRT 0.0342  Fuzzy AHP 0.0348  AHP Linear 0.0713  AHP Power 0.0999  AHP Root Square 0.0546  AHP Geometric 0.0775  AHP Inverse Linear 0.0478  AHP Asymptotical 0.0028  AHP Balanced 0.0511  AHP Logarithmic 0.0589</td>
<td></td>
<td>0.9394</td>
</tr>
<tr>
<td></td>
<td>Employees (sc4)</td>
<td>Fuzzy IRT 0.0324  Fuzzy AHP 0.0346  AHP Linear 0.0695  AHP Power 0.0962  AHP Root Square 0.0539  AHP Geometric 0.0794  AHP Inverse Linear 0.0479  AHP Asymptotical 0.0038  AHP Balanced 0.0513  AHP Logarithmic 0.0577</td>
<td></td>
<td>0.9421</td>
</tr>
<tr>
<td></td>
<td>Suppliers (sc5)</td>
<td>Fuzzy IRT 0.0328  Fuzzy AHP 0.0356  AHP Linear 0.0649  AHP Power 0.0835  AHP Root Square 0.0521  AHP Geometric 0.0744  AHP Inverse Linear 0.0480  AHP Asymptotical 0.0044  AHP Balanced 0.0510  AHP Logarithmic 0.0551</td>
<td></td>
<td>0.9502</td>
</tr>
<tr>
<td></td>
<td>Media (sc6)</td>
<td>Fuzzy IRT 0.0392  Fuzzy AHP 0.0389  AHP Linear 0.0520  AHP Power 0.0547  AHP Root Square 0.0466  AHP Geometric 0.0487  AHP Inverse Linear 0.0422  AHP Asymptotical 0.0034  AHP Balanced 0.0434  AHP Logarithmic 0.0485</td>
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<td>0.9642</td>
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<td>Motivations - Criterion 2</td>
<td>Image improvement (sc7)</td>
<td>Fuzzy IRT 0.0446  Fuzzy AHP 0.0419  AHP Linear 0.0439  AHP Power 0.0400  AHP Root Square 0.0427  AHP Geometric 0.0381  AHP Inverse Linear 0.0400  AHP Asymptotical 0.0033  AHP Balanced 0.0403  AHP Logarithmic 0.0437</td>
<td>0.9734</td>
<td>0.9671</td>
</tr>
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<td>Marketing opportunities (sc8)</td>
<td>Fuzzy IRT 0.0405  Fuzzy AHP 0.0400  AHP Linear 0.0462  AHP Power 0.0444  AHP Root Square 0.0438  AHP Geometric 0.0456  AHP Inverse Linear 0.0421  AHP Asymptotical 0.0058  AHP Balanced 0.0431  AHP Logarithmic 0.0447</td>
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<td>0.9764</td>
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<td>Cost reduction (sc9)</td>
<td>Fuzzy IRT 0.0383  Fuzzy AHP 0.0389  AHP Linear 0.0453  AHP Power 0.0439  AHP Root Square 0.0433  AHP Geometric 0.0464  AHP Inverse Linear 0.0418  AHP Asymptotical 0.0075  AHP Balanced 0.0427  AHP Logarithmic 0.0440</td>
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<td>0.9709</td>
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<td></td>
<td>Differentiation from competitors (sc10)</td>
<td>Fuzzy IRT 0.0444  Fuzzy AHP 0.0431  AHP Linear 0.0366  AHP Power 0.0275  AHP Root Square 0.0390  AHP Geometric 0.0301  AHP Inverse Linear 0.0384  AHP Asymptotical 0.0057  AHP Balanced 0.0377  AHP Logarithmic 0.0389</td>
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<td>Low-carbon products - Criterion 3</td>
<td>Use of life cycle assessment (carbon footprint) (sc11)</td>
<td>Fuzzy IRT 0.0269  Fuzzy AHP 0.0328  AHP Linear 0.0524  AHP Power 0.0573  AHP Root Square 0.0466  AHP Geometric 0.0683  AHP Inverse Linear 0.0477  AHP Asymptotical 0.0271  AHP Balanced 0.0508  AHP Logarithmic 0.0474</td>
<td>0.9978</td>
<td>0.9829</td>
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<td>Use of renewable and/or recycled raw materials – (sc12)</td>
<td>Fuzzy IRT 0.0418  Fuzzy AHP 0.0405  AHP Linear 0.0337  AHP Power 0.0250  AHP Root Square 0.0372  AHP Geometric 0.0295  AHP Inverse Linear 0.0370  AHP Asymptotical 0.0099  AHP Balanced 0.0367  AHP Logarithmic 0.0367</td>
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<td>0.9974</td>
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<td>Reduction of carbon emissions in utilization phase (sc13)</td>
<td>Fuzzy IRT 0.0316  Fuzzy AHP 0.0361  AHP Linear 0.0417  AHP Power 0.0371  AHP Root Square 0.0414  AHP Geometric 0.0475  AHP Inverse Linear 0.0431  AHP Asymptotical 0.0376  AHP Balanced 0.0444  AHP Logarithmic 0.0411</td>
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<td>Measurement of carbon emissions in</td>
<td>Fuzzy IRT 0.0315  Fuzzy AHP 0.0354  AHP Linear 0.0406  AHP Power 0.0359  AHP Root Square 0.0408  AHP Geometric 0.0473  AHP Inverse Linear 0.0430  AHP Asymptotical 0.0576  AHP Balanced 0.0444  AHP Logarithmic 0.0403</td>
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## Low-carbon processes - Criterion 4

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<th>Description</th>
<th>Values</th>
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<td>Use of energy/carbon efficient equipment (sc15)</td>
<td>0.0436 0.0414 0.0265 0.0157 0.0330 0.0209 0.0343 0.0197 0.0327 0.0316</td>
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<td>Use of low-carbon/carbon-free energy sources (sc16)</td>
<td>0.0351 0.0375 0.0312 0.0219 0.0357 0.0310 0.0378 0.0631 0.0377 0.0344</td>
<td>0.9853</td>
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## Low-carbon logistics - Criterion 5

<table>
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<th>Description</th>
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<th>Average</th>
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<tbody>
<tr>
<td>Measurement of carbon emissions from transportation processes (sc17)</td>
<td>0.0280 0.0338 0.0356 0.0274 0.0382 0.0398 0.0417 0.1335 0.0426 0.0370</td>
<td>0.9348</td>
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<tr>
<td>Consolidation of shipments to reduce carbon emissions (sc18)</td>
<td>0.0348 0.0370 0.0287 0.0187 0.0341 0.0281 0.0373 0.0988 0.0368 0.0325</td>
<td>0.9155 0.9516</td>
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<td>Use of carbon-efficient technologies and modes of transportation (sc19)</td>
<td>0.0274 0.0337 0.0318 0.0220 0.0361 0.0343 0.0401 0.2044 0.0404 0.0345</td>
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## Low-carbon performance over the past three years - Criterion 6

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</tr>
</thead>
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<tr>
<td>Energy per unit produced (sc20)</td>
<td>0.0488 0.0421 0.0158 0.0052 0.0256 0.0083 0.0283 0.0123 0.0248 0.0234</td>
<td>0.9284</td>
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<tr>
<td>CO2 emissions per unit produced (sc21)</td>
<td>0.0472 0.0424 0.0153 0.0049 0.0253 0.0083 0.0285 0.0148 0.0249 0.0229</td>
<td>0.9299 0.9316</td>
</tr>
<tr>
<td>Use of CO2-intensive raw materials (sc22)</td>
<td>0.0472 0.0432 0.0144 0.0043 0.0245 0.0077 0.0280 0.0173 0.0244 0.0219</td>
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## Barriers - Criterion 7

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<tr>
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<tr>
<td>There is a social and consumer context that does not encourage the reduction of CO2</td>
<td>0.0447 0.0407 0.0150 0.0053 0.0247 0.0091 0.0280 0.0511 0.0250 0.0222</td>
<td>0.9123 0.9329</td>
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<tr>
<td>emissions by the company (sc23)</td>
<td>0.0394</td>
<td>0.0392</td>
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<tr>
<td>-----------------------------------------------------------------------------------------------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>There is an internal organizational culture that does not encourage the reduction of CO₂ emissions where I work (sc24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>There is a political and governmental context that does not encourage the reduction of CO₂ emissions where I work (sc25)</td>
<td>0.0473</td>
<td>0.0426</td>
</tr>
<tr>
<td>It is difficult to include the topic of reducing CO₂ emissions where I work (sc26)</td>
<td>0.0435</td>
<td>0.0418</td>
</tr>
</tbody>
</table>